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DEEP: A model of gaming preferences informed by the hierarchical nature of goal-oriented cognition

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ABSTRACT

Video game design and player engagement revolve around the concept of agency, which refers to the ability to shape one's environment through personal choices and actions. However, different types of agentive experiences can be distinguished according to the nature of the agent's goal. Recent models of voluntary action suggest that goals are organized hierarchically. In this paper, we test the ability of these models to explain variability in gaming preferences. First, we performed a factor analysis on game-related actions that participants (N = 750) were asked to rate on an interest scale. We found that game preferences varied along 4 dimensions organized along gradients of goal abstraction and exploration (Discovering, Experimenting, Expanding, Performing, or DEEP dimensions). We then automatically annotated video games (N = 16,000) on each of these dimensions and tested the hierarchical structure of goal-directed actions in video games. Finally, in a pre-registered study (N = 1000), we show that the DEEP dimensions predict participants' preferred video games and correlate with expected psychological factors. We suggest that this research can help improve existing taxonomies of videogame types, better understand player preferences, and refine the relationship between game design and human psychology.

1. Introduction

Video games have become the leading entertainment industry with over 3.2 billion gamers worldwide and with an annual revenue reaching over 180 billion dollars in 2022 (Newzoo, 2022). The considerable cultural success of video games as a new form of interactive entertainment has generated a significant amount of academic works in a variety of disciplines, from psychological research on digital media to narrative and computer science studies, human–computer interaction research, and evolutionary psychology (e. g., [15,90,97,106;107,113,114,150,151,153,154,162]. At the heart of many of these works lies the notion of agency, which is the "satisfying power" to make things happen through one's own choices and actions ([108]. This focus on agency comes as no surprise: you cannot fully understand the thrill of a game without directly interacting with it as an agent.

It is commonplace to say that interactivity is a defining feature of video games. Video games are virtual environments coupled with a controllable interface, offering the user the possibility of making active choices, which in turn enable them to exert a significant influence on external events. Agency refers to this ability to influence events intentionally, and video games are, of all recreational media, and perhaps of all human activities, the ones that make the most of this ability. People find video games attractive because they engage with our propensity to "decide and do" [113], that is, to take actions in a dynamically responsive world [77;108]. In other words, people repeatedly come back to video games because game mechanics are specifically tuned to amplify player agency, i.e. the player's ability to influence the game environment through the game design or mechanics [18,141,153].

However, agency, like action, intention, or goal, is not a unitary concept. Indeed, it goes for video games as it does for real life: there are many ways of interacting with the world and one can experience different ways of being an agent. Some authors have rightly acknowledged the diversity of agentive experiences in video games (e.g., "layered agencies", [113]; "agency scope", [60]; "micro" vs. "macro-involvement"; [70]. Yet, there has been no explicit attempt to map these experiences onto the various types of actions or goals that a game allows one to perform or pursue. We believe that a better characterization of this mapping between action and experience can make three significant contributions to the field, by showing (1) that the space of gaming

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preferences is structured by players' preferences for varying types of agency, (2) that these agentive preferences can help refine existing taxonomies of video game genres and types, and finally, (3) that these preferences are ultimately rooted in broader, deep-seated psychological factors. This fine-grained mapping of action and experience should also enable game designers to better identify the specific game elements that elicit player enjoyment, and players to better understand their own preferences.

2. The hierarchical nature of goal-oriented cognition

Explaining the link between agency and gaming preferences requires careful consideration of recent models of *goal-directed* action in cognitive science [24,55,56,109]; see also [126]. A goal can be defined as an internal representation of a desired end-state. This representation can be of sensorimotor type (e.g., taking a glass), with the desired end-state represented directly in terms of the motor commands needed to achieve it. This motoric format is directly suitable for action execution. But goals can also be defined as higher-order representations (e.g., quenching one's thirst), the achievement of which may involve the completion of several motoric subgoals (e.g., grasping a glass, opening a tap, filling the glass, etc.). Such higher-order goals include a future-directed component and do not necessarily contain any reference to the practical (e.g., motoric) means required to achieve them [118].

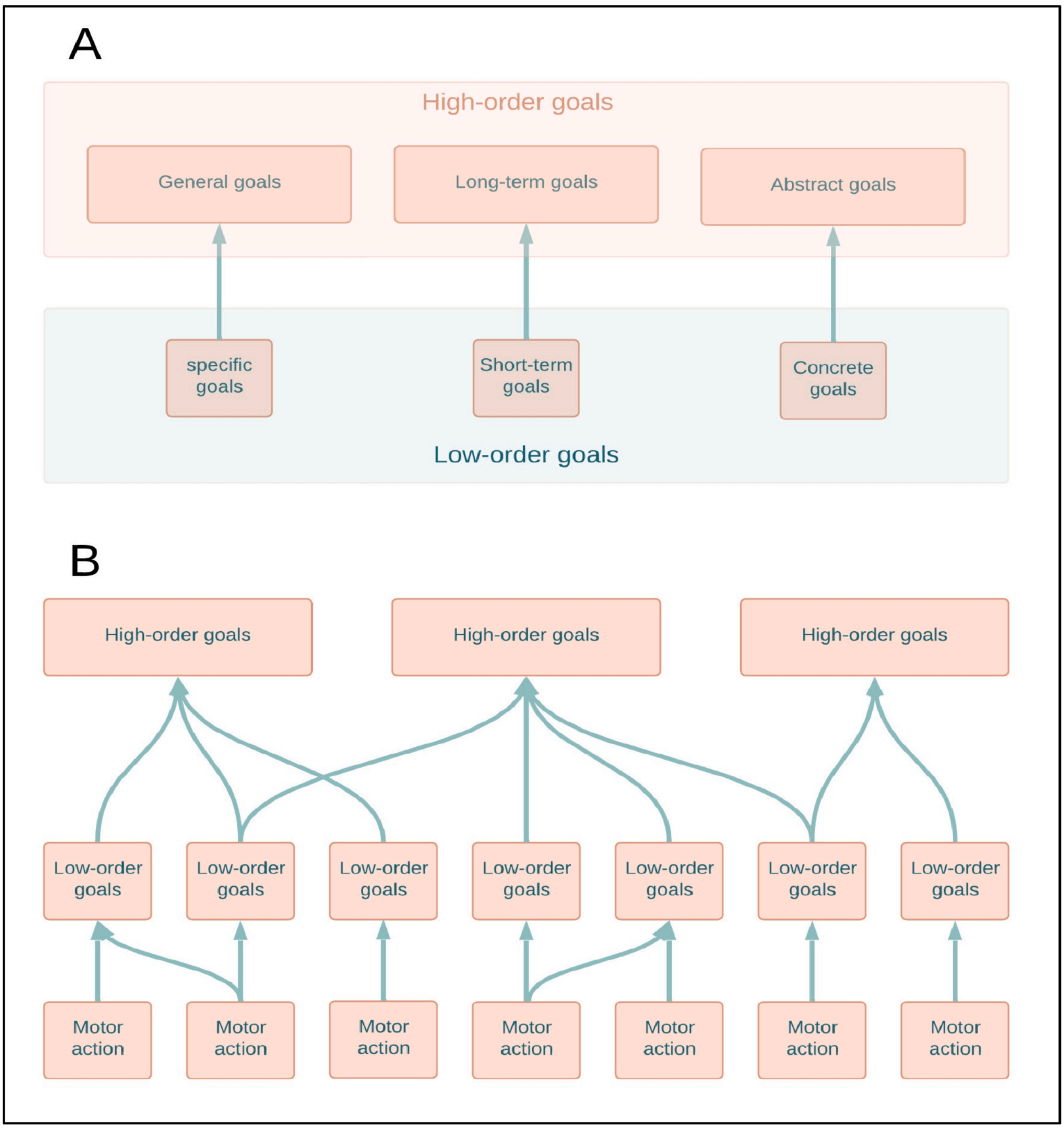

Fig. 1. A. Gradient of goals. Cognitive scientists have long recognized that goals are not of a single type, but can be broken down into different hierarchically organized types and subtypes. In this hierarchy, high-order goals tend to be general, long-term oriented, and abstract, while low-order goals tend to be specific, short-term-oriented, and concrete. **B. Schema of the hierarchy of goal-oriented actions**. Motoric actions are associated with low-order goals mostly in a one-to-one correspondence, while high-order goals can be associated with multiple low-order goals (many-to-many correspondence).

In this model, goals are not of a single type but are multiple and hierarchically organized along a gradient from concrete to abstract. The abstraction dimension affords to capture three characteristic features of goal representations, namely their specificity (i.e., specific vs. general), their temporal scale (i.e., short- vs. long-term), and their relation to the current requirements of action specification and control (see Fig. 1**.A.**). Note that goals can vary along several other dimensions that we will not consider here, such as their commitment (i.e., low vs. high commitment), their difficulty (i.e., challenging vs. easy), and their level of consciousness (i.e., conscious vs. unconscious; see [94].

The position of the goal along this gradient depends on its relationship with the action required to achieve it [24], 2017). This relationship, or mapping, can be more or less direct. Near the bottom of the hierarchy, "low-order" goals (e.g., 'pressing a keyboard button') have a one-to-one mapping with the corresponding action (e.g., pressing), while "high-order" goals (e.g., 'saving a document') have a many-to-many mapping with the actions required to achieve them (see Fig. 1**.B.**). In other words, while there is often only one possible way to achieve a low-order goal, different actions can be implemented to achieve a similar high-order goal (e.g., 'saving a document' by either clicking an item on a menu or typing a keyboard command) and conversely, the same action (e.g., pressing a button) can achieve different high-order goals (e.g., 'saving a document' vs. 'writing in a document').

This complex mapping of goal and action is a direct consequence of the hierarchical organization of goal representations: the lower the goal is represented in the hierarchy, the more it is "executable" (i.e., represented in a format that is directly suitable for action execution). Lower-order goals are called "concrete" because they are encoded in such a practical format, which allows for the immediate selection of appropriate motor patterns once an action is planned or selected. In contrast, higher-order goals are said to be "abstract" because their content is general and descriptive, and they therefore make no explicit reference to the motoric means or sub-goals required to achieve them (e.g., 'living a happy life').

Importantly, this flexibility of content makes it possible for an agent to form a high-order intention to perform an action even though the present situation does not allow its immediate performance. Higher-order goals are therefore in principle detachable from the agent's current situation [119]. Thus, unlike lower-order goals that operate at the time scale of action execution, higher-order goals can extend far into the future, and hence, have greater temporal flexibility: one can form a high-order intention to act an hour from now, or tomorrow, or next week, and so on. For the sake of parsimony, we reduce the hierarchy of goals here to a binary distinction between low- and high-order goals, but the hierarchy is obviously better described as a continuum, with multiple intermediate layers (see [119], for a three-tiered dynamic model of goal-directed actions).

Another critical feature of the goal hierarchy is the strong interdependence of its levels. Goals are embedded within each other, meaning that a low-order goal is often a means for achieving a higher-order goal, while higher-order goals often determine the motivational value of lower-order goals [20,38,65]. In this view, not only are the characteristics of a goal a function of its position along the hierarchy (from concrete to abstract), but its characteristics also depend on the nature and strength of its ties to other goals in the hierarchy. Thus, a similar action can be described at various levels of goal representation (e.g., 'turning a doorknob' vs. 'opening the door' or 'leaving a room'; see [155] but it is also characterized by the specific connections that lower- and higher-order goals may have with each other within the behavioral sequence ('opening a door' by turning a doorknob or by pushing it). Note, however, that this in no way implies that all actions can be described at multiple levels of the hierarchy, or that all actions necessarily mobilize the entire goal hierarchy, as simple actions such as motor routines demonstrate.

Recognizing that actions are organized hierarchically according to their level of abstraction (or the time horizon of the goals they achieve) sheds new light on the so-called "exploration exploitation" trade-off (on this trade-off; see: e.g., [30,63,102]. This trade-off can be thought of as a continuum along which behaviors vary, from exploitation (of known behavioral strategies) to exploration (of new strategies). As such, it can readily be applied to goal-oriented actions. Thus, organisms may aim to *exploit* existing associations between goals at various levels of the hierarchy, whether cognitively hardwired or previously learned. But organisms can also aim at flexibly *exploring* new associations between motoric actions and low-level goals, or between low-level and higher-level goals along the hierarchy [56,66,29]. Importantly, acknowledging the existence of goal hierarchies makes it possible to conceive of exploratory behaviors as fundamentally *goal-oriented*, i.e., as behaviors aimed at discovering new goals or new connections between low-level and high-level goal representations.

Both the goal hierarchy and the exploitation-exploration tradeoff can be viewed as essential dimensions of voluntary behaviors in complex environments. In what follows, we build on these two critical dimensions to define a conceptual framework from which distinct instrumental motivations, or motivations for action, can be derived. These motivations form the cells of a two-by-two table (i.e., low-level exploitation; high-level exploitation; low-level exploration; high-level exploration) which we describe in detail in the following subsections.

2.0.1. Performing: Low-order exploitative goals

As mentioned above, the existence of basic, automatic, or routine actions suggests that some of our behaviors are simply aimed at realizing low-level goal representations – where the goal is described in terms of the practical means (e.g., motoric) needed to achieve it. For sensorimotor actions as basic as "grasping" or "reaching" an object, for example, the goal representation is used to guide the selection of appropriate motor patterns (e.g., adapting the shape and size of the grip to the targeted object), but can also organize the motor sequence according to the higher-order goal of the action (e.g., adapting the grip to the use that one wants to make of the targeted object; [119]. Importantly, recognizing the existence of such low-level goal representations helps to understand why people sometimes engage in *voluntary* activities that seem devoid of any meaningful (high-level) goal, such as bouncing a ball repeatedly off a wall. Here, the motivation to engage in the activity does not come from satisfying higher-order objectives, but from the need to experience "competence", that is, a sense of mastery in ***performing*** simple, familiar actions with known outcomes [135,159]. This sense of mastery is clearly illustrated by the satisfying experience of exploiting skills already acquired, such as solving a Rubik's Cube or crafting some tool (see bottom right of Fig. 2).

Recognizing that behaviors can be simply motivated by *exploiting low-order goal representations* offers a potential to explain games based on simple motor commands (e.g., *Super Hexagon*). It also sheds light on the enjoyment players derive from repeating familiar low-level goal-driven actions with anticipated outcomes, which is evident in genres such as multiplayer battle arenas, first-person shooters, and classic arcade games. Some authors go so far as to suggest that the specific content of games – whether shooters or puzzle-solvers – may be secondary to the interaction mechanics themselves when it comes to satisfaction (Przybylski, 2009). Without endorsing such a radical perspective, it is worth noting that people can get pleasure from simply pressing a button repeatedly, just as a player can enjoy experiencing "competence" in quickly pressing the left and right buttons on a controller, or in quickly rotating figures in space to make them fit perfectly [6,131,136], as famously illustrated by the blockbuster game *Tetris*. Even in sandbox games, some players enjoy sticking to their preferred weapon or tool and repeatedly use them, demonstrating a form of satisfaction derived from experiencing highly predictable low-level action-outcome associations.

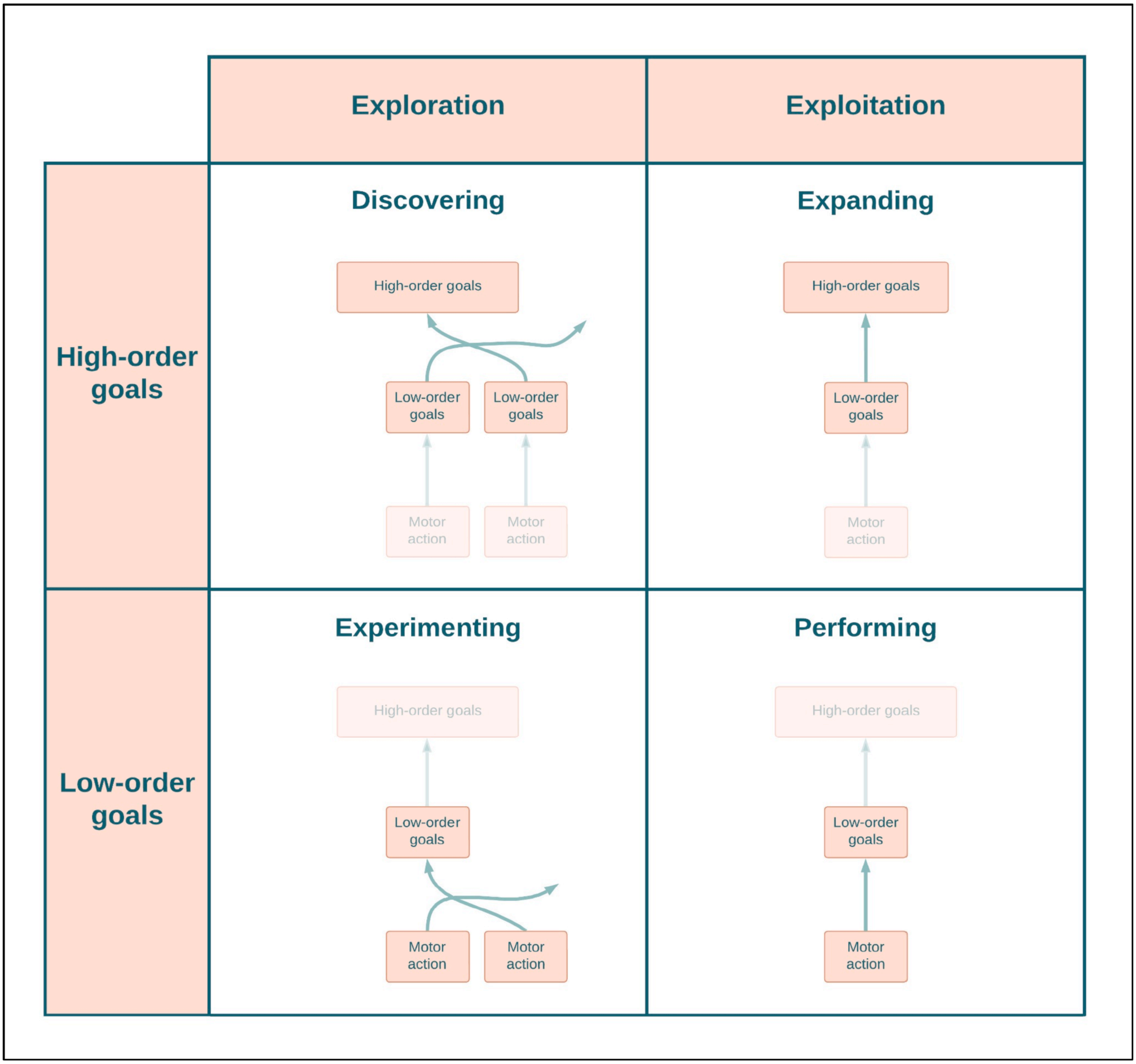

Fig. 2. Defining features of goal hierarchies. Goals can be either high- or low-order and can be exploitative or explorative. Four key strategies emerge, which correspond to four types of gameplays and are associated with distinct types of game experience. A preference for one strategy corresponds to a preference for exercising one particular form of agency. In each cell of the table, the satisfaction is derived from the achievement of actions and goals (represented by the blue arrows). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

2.0.2. Experimenting: Low-order explorative goals

Low-level *exploitative* actions can be distinguished from low-level actions that aim at ***experimenting*** with new associations between motoric actions and (unfamiliar) low-level goals. This is well exemplified in children's playful exploratory behaviors, where the only drive is to perform basic actions (e.g., 'knocking something off a table', 'putting a finger in a candle') whose goal is not always obvious or clearly identifiable. As such, playful exploratory behavior is a type of behavior which appears incompletely functional, compared with its use in a normal, functional context [17]. Note that this form of play is not unique to humans, but also seem to be present in other animal species, especially in non-stressful, relaxed contexts [3,15,50,117,121].

Playful behaviors, however, are not without purpose. There is some evidence to suggest that they serve a learning function, promoting the acquisition of incidental associations between basic actions (e.g., 'knocking something off a table') and indeterminate action-contingent events (e.g., 'opening a nut'). Once learned, these incidental associations can then be *intentionally* used for pursuing desirable outcomes, that is, for achieving goal-directed behaviors (e.g., [47]; see also [12,142]; see bottom left of Fig. 2). For instance, rats that have experienced play with their peers during their juvenile period exhibit enhanced maze navigation skills, greater impulse control, and better coordination with a social partner compared with rats that have been deprived of such experience [4]; A. P. [68,120]; see [121]. It is not surprising, then, that playful exploration behaviors are more common in young animals, which have less experience with action-outcome contingencies and thus have a greater need to learn [143] (see also [44]). At the extreme, "motor babbling" in infants (i.e., the process of executing seemingly random movements) can be seen as the first manifestation of playful exploratory behavior, the useful consequence of which is the incidental acquisition of novel action-outcome relationships (see [83]).

Such associative learning processes are intrinsically pleasurable, even in an entertaining or fictional context. For instance, some players of games with multiple characters, such as *League of Legends* or *Super Mario Bros.*, enjoy changing characters often: each time, they get the pleasure of learning to master basic actions to pursue low-level goals, without the need for higher-order goals. This is also consistent with the fact that some players like to constantly experiment with new moves or combos, continually adapt their strategies to the task in hand or discover new, practical ways of playing (commonly known as "overachievers"). Arguably, Video game tutorials precisely serve this purpose: to help players learn and master low-level commands so that they can explore the relationships between these commands and simple, low-level objectives, such as moving from one point to another or manipulating objects. It is telling, then, that in some video games, new tools or weapons are introduced at regular intervals, creating a dynamic environment that continually challenges players to adapt to fulfill their low-level goals (e.g., *It Takes Two*). This cyclical pattern of introducing new elements effectively keeps the player in a perpetual state of experimentation. Within this cycle, the game acts as a continuous tutorial, constantly teaching new mechanics or strategies – a design approach that exploits the intrinsic pleasure derived from learning and mastering new skills.

2.0.3. Expanding: High-order exploitative goals

At the top of the goal hierarchy, representations are endowed with general and descriptive contents, which make high-level goals less constrained by the pressing demands of action specification and control, as low-level goals can be [119,109]. This also makes high-order goals rather impervious to external interference, and less likely to be updated or revised in the long run (e.g. [23]. This relative *stability* of higher-order goals is a notion that fits rather well with our intuition: the higher the goal is within the hierarchy, the more costly it is to modify its content (e.g., 'going to the restaurant' vs. 'cooking a three-course menu'), and conversely, the lower the goal, the less difficult it is to substitute another one (e.g., 'eating with chopsticks' vs. 'eating with a fork').

The stability of higher-order goals is an essential requirement for implementing long-term behaviors, which require a certain continuity of intent [22,45] (see [65], for a review). In video games, such continuity is made possible by the game design itself: higher-level goals are those goals that are usually set in advance ("designated", [113]) by the designer, and shaped by hard constraints such as the game world or the story itself. The pursuit of higher-order objectives thus often requires the player to follow the game's narrative nodes, as instantiated in the "quests" or in the various ways the game has of exposing its backstory, either through the dialogues and behaviors of key Non-Playing Characters (NPC), or through non-playable animated or live-action sequences (the so-called "event scenes"; [151]). Exploiting the high-level objectives of a game, then, often comes down to ***expanding*** one's knowledge of the game's world and story and getting pleasure from the experience (see top right of Fig. 2).

Linear gameplays with clearcut "end-states" are indeed very mainstream (e.g., the *Mario* series, *Tomb Raider*). More generally, the attraction to decisions associated with a game's highest designated goals is demonstrated by the existence of many successful games with branching decision-based stories (e.g., *Life is Strange*). Even in sandbox open-world video games, some players enjoy watching the cinematics that further develop the story or following the quests in the order that seems to have been planned by the designer.

2.0.4. Discovering: High-order explorative goals

High-level goal-directed cognition does not always exploit existing relationships between lower- and higher-order goals. It sometimes aims to explore new ones by *relaxing* these existing relationships, and by pursuing lower-order goals that are no longer attached to particular superordinate goals [56] (see also [64]). As mentioned earlier (see "Low-level explorative goals"), you can enter into exploration *accidentally*, for example by pressing the wrong button unintentionally and realizing that it produces an effect previously unknown. Similarly, new relationships between lower- and higher-order goals can be found while performing basic actions just for the sake of performing them, as in children's playful behaviors.

But exploratory behaviors can also be triggered *intentionally*, through what is known as "self-directed" exploration [58]. In self-directed exploration, an agent decides to actively loosen the usual connections between goals at multiple levels. The reasons for self-directed exploration are multiple: one can decide to enter into exploration either out of curiosity, or for fun, or with the more explicit intention of ***discovering*** new connections and, ultimately, reorganizing the goal hierarchy (see top left of Fig. 2). Thus, when driving home one may choose a different route from the usual one and discover new opportunities along the way (e.g., by stopping at an art gallery or a café; [56]). Here, exploration consists in losing the usual connection between a low-order (e.g., driving) and a high-order state (e.g., going home) so as to discover a new superordinate goal (e.g., stopping at a cafe). This new high-order goal can now be associated with the low-order state through a new connection that reorganizes the goal hierarchy.

Many recent video games examples illustrate this propensity to 'freely' explore new associations between goals at different levels of the hierarchy, or to divert known low-level strategies to discover, or even define, as yet unknown higher-order objectives. This need for discovery is perfectly illustrated by the pleasure some players take in exploring open-worlds in which higher-order objectives can be discovered, if not invented, by the players themselves. While this is ultimately an empirical question, there is anecdotal evidence to suggest that the content of video games increasingly encourages such exploratory behaviors: it is well exemplified by the apparent high cultural success of sandbox games, that is, of games that provide players with a great degree of apparent freedom and creativity, with no clear predetermined goal (e.g., *Minecraft*, *Sims*, *Animal Crossing*) or with goals that players set themselves in a nonlinear fashion (e.g., *Grand Theft Auto V*, *Elden Ring*, *Zelda*). In video games of this kind, some gamers enjoy discovering new places, unlocking the map progressively, having the freedom to do the quests in any order they like, or simply wandering out at their own pace. One of the best examples is *No Man's Sky*: in this open-world survival Video game, game mechanics did not constrain gamers to follow clear, "designated" high-order goals.

2.0.5. Summary

Here, we take that *Performing* (i.e., *exploiting low-level* action-outcome associations), *Experimenting* (i.e., *exploring low-level* action-outcome associations), *Expanding* (i.e., *exploiting high-level* action-outcome associations), and *Discovering* (i.e., *exploring high-level* action-outcome associations), are four different dimensions of goal-directed actions and self-agency (Fig. 2). Importantly, in this model, each type of action can be implemented for its own sake, and thus a preference for exercising one form of agency is not necessarily predictive of a preference for another. In what follows, we present the construction and validation of a questionnaire designed to capture this variability in agentive preferences, and whose dimensions are shaped by our hierarchical model of goal-directed action.

From this theoretical background, 4 main hypotheses were derived:

- H1: Gamers' preferred actions in video games should cluster along 4 dimensions that should align with the dimensions generated by our theory. We test this prediction in **Section 3**.
- H2: Video games should exhibit a nested pattern where games that help achieve high-level goals also help achieve low-level goals, but not necessarily vice versa. We test this prediction in **Section 4**.
- H3: Gamers' scores on the DEEP questionnaire should predict which video games they prefer, according to the four DEEP dimensions. We test this prediction in **Section 5**.
- H4: Following recent works in behavioral ecology and personality psychology, we predict that gamers' scores on the DEEP questionnaire should be associated with particular personality traits and socio-demographic factors. We test these predictions in **Section 6**.

3. Study 1: The elaboration of the DEEP questionnaire

We leveraged both Exploratory Factor Analysis (EFA) and Confirmatory Factor Analysis (CFA) to specifically test the idea that goal hierarchies can successfully capture the variety of gamers' preferences and video game content. In the process, we aimed to validate a measurement instrument for describing and quantifying preferred action representations (and underlying goal orientations) in video games, in line with the psychology underpinning human enjoyment associated with interactive entertainment devices. The underlying goal here was to identify the smallest number of latent dimensions, or factors, behind people's preferences for exercising certain types of agency in video games. In this way, we followed the idea that scale validation is an integral component of theory-testing [145].

Many psychometric scales designed to measure gamers' motivations and preferences have been proposed recently in an effort to refine Bartle's original taxonomy of players (see [165], for a gamer self-identification scale; see [87], for a systematic review; see [36] for a systematic review of player experience questionnaires). Some of these scales have focused on single video games, single genres (see [33] for a review), or single themes (e.g., the BFI-G, which identifies preferred levels of agency in video games, but primarily for violent actions [49]). Other scales, more extensive, and originating in self-determination theory [150], have used self-reported preferences to explore the different motivations to engage in digital play, with emerging factors such as 'Autonomy', 'Social relatedness, or 'Competence' (e.g., [33,62,78]). Such scales have the advantage of being very broad and encompassing, as they include many items on the various potential motivations that seem to be often reported by gamers and inform us about their *explicit* gaming preferences.

However, gamers' reflections on their own *motivations* and *preferences* may conceal underlying preferences that are more unconscious or difficult to pin down. Because, at the intuitive level, the content of what triggers cognitive preferences is not self-evident, people often find it difficult to explain why they enjoy an activity and may end up finding post-hoc justifications for it, which may be heightened by experimental biases (e.g., "social desirability bias"; see [42]). For instance, it is not clear why people would play video games to escape the real world or to interact socially. Why would a video game be the best tool to achieve such goals? Instead, people could read stories or watch movies to escape from their daily lives, and they could use parties or social networks to connect socially with other people. We therefore propose to test the theory that the specificity of the enjoyment for video games lies in agency, and only agency, by designing the first scale based on the cognitive framework of hierarchical models of goal-directed actions. In an attempt to 'bypass' people's reflexive thoughts about their own *motivations* and *preferences*, our strategy is to use much finer-grained gaming *actions* that will be rated by participants on an interest scale.

3.1. Method

Factor analysis is a statistical method used to uncover the underlying structure of a large set of variables. By analyzing the relationships among these variables, factor analysis seeks to identify a smaller set of latent dimensions, or factors, that can explain these observed relationships. In essence, factor analysis is a data-driven approach that clusters variables together without direct intervention by the experimenter. In this work, we conducted a factor analysis on a large number of items regarding the type of agency (i.e., the type of actions, choices, or strategies) that gamers like to exercise when playing video games. We were interested in how these items clustered, whether they clustered in a manner consistent with our theoretical framework, and whether it was possible to use the latent dimensions of this analysis (along which the items clustered) to predict gamers' explicit video game preferences and more finely characterize the content of the video games themselves.

3.2. Participants

We recruited 750 participants from the United-States through the online research platform Prolific. Our sample size was determined by a common heuristic used for factor analysis: a subject-to-item ratio of 10:1 [89,115]. Because our factor analysis included 68 items, our sample size had to be greater than 680. After excluding 19 participants who failed the attention check, we ran the analysis on 732 participants (361 males, 362 females, 8 non-binary/third gender, 1 'prefer not to say'; $M_{age} = 36.1$, $SD_{age} = 11.3$). Participants reported playing on average 12 Video games in the past year ($SD_{n\_vg} = 10.93$) and playing an average of 12 h per week ($SD_{h\_vg} = 10.91$).

3.3. Item generation

We generated a large set of items ($n = 68$) in three distinct steps. First, we derived 30 items that could be described along gradients of abstraction and exploration. Then, we conducted an initial exploratory analysis of these 30 items on 350 participants, to test both item relevance and scale design. Next, we conducted informal interviews with gamers, presenting them with the original list of items and asking them what goal-oriented actions might be missing from the list, based on their gaming experiences. These interviews increased the number of items from 30 to 50. Finally, we systematically organized the set of items according to the four types of agency identified by the theory (i.e., Performing, Experimenting, Discovering, Expanding), so as to obtain, in principle, a balanced number of items for each type. For instance, "Using the same tool or weapon over and over again" is an item that seems to be linked to the Performing dimension, and we expected it to cluster with other items such as "Maintaining my strategy no matter what until it works". We ended up with 68 items, such as 'Watching the cinematics that explain the backstory', 'Maintaining my strategy no matter what until it works', 'Discovering new places' and 'Trying out new ways of using my weapons or tools' (see Supplementary Materials for the full list of items).

3.4. Experimental design

After answering demographic questions and questions related to their general gaming habits, participants were asked to rate the 68 items on an interest-based scale (1: 'Not at all interested'; 2: 'Not very interested'; 3: 'Slightly interested'; 4: 'Neutral', 5: 'Moderately interested', 6: 'Very interested'; 7: 'Extremely interested'). They could also choose to answer that the item did not apply to their gaming habits in case they did not play any Video games related to that item. The order of the items was randomized for each participant.

3.5. Data processing

3.5.1. Imputation method

As we included the option of answering 'Does not apply' to each item, we had to handle missing values. A common way to handle missing data is to simply delete any row or column that contains missing values. However, this method can result in a significant loss of data and bias the results of the analysis. An alternative approach is to supplement the missing values with estimates based on the available data, through a computational process called 'imputation'. To do this, as pre-registered, we first removed 57 participants who had rated less than 95 % of items and were therefore likely to be non-gamers (a 5 % threshold of missing values being a common prerequisite to perform data imputation). Following the same rule of thumb, we deleted 4 items that exceeded the same 5 % missing values threshold (and were therefore likely to be ill-posed). After exclusion, the sample size was reduced to 675 participants, and the pool of items to 64, for subsequent analysis. We then imputed data using the 'Mice' package (method: 'pmm', seed:500) to algorithmically fill in missing data. This involved creating multiple imputed datasets by fitting a separate model to each column containing missing values and using that model to predict those missing values.

3.5.2. Removal or redundant items and outliers

We removed 3 redundant items (i.e., correlations between items greater than 0.7). Next, we removed 53 participants who were outliers (using the Mahalanobis distance; $X^2(64 = 8567.66)$). Therefore, the final number of items was 61 and the final sample size was 622 participants. This still ensures enough statistical power to perform a factor analysis. Data were then inspected for multivariate assumptions.

3.5.3. Selection of extraction method

We used the Bartlett test of sphericity and the Kaiser-Meyer-Olkin (KMO) test to verify that the data would benefit from factor analysis. The Bartlett test indicated that the items are overall related to each other, rejecting the null hypothesis that the correlation matrix is an identity matrix ($X^2(1830) = 19358.08$, $p < 0.001$). The KMO value was 0.96, indicating the presence of a strong partial correlation ('marvelous' sampling adequacy). Taken together, these pre-processing analyses show that the data are suitable for exploratory factor analysis.

3.5.4. Parallel analysis

A Parallel Analysis [67,91] showed that the first five factors had eigenvalues of 18.39, 2.86, 1.96, 1.47, and 1.18 (while the sixth factor had an eigenvalue of 0.82, below the Kaiser criterion that an eigenvalue must be greater than 1). Visual inspection of a scree plot supported an initial five-factor model. The presence of a high first eigenvalue suggests that there is a strong underlying factor in the data that explains much of the variance.

3.6. Results

We then performed an Exploratory Factor Analysis (for a review and test of this statistical method, see [2]). We used the 'promax' rotation method, which is a type of oblique rotation that allows factors to be correlated with each other. Therefore, it allows for a more flexible solution that can better fit the data.

After the first factor analysis, we removed 4 items whose communalities were below 0.2 [31,158]. Then, successive iterations of the same method led to the deletion of additional items, either because they had communalities below 0.2 or because they loaded on multiple factors with a difference between these loadings lower than 1 (see [84,124,149]). Removal of items was done one by one (see [2]). After three iterations, we reduced the number of factors from 5 to 4, because at this stage of the process, the fifth factor consisted of less than 3 items with loadings above 0.32. With further iterations, we eventually removed 4 more items following the same logic.

We ended up with a stable factor analysis (i.e., no item loading lower than 0.2 and no cross-loading) with 51 items loading on 4 factors. No additional items were removed. Quality-of-fit metrics indicated an adequate (i.e., moderate to good) fit, with an RMSEA of 0.051 (90 % CI [.048, 0.053]), an RSMR of 0.04, and a Tucker Lewis Index (TLI) of factoring reliability of 0.86. This factor analysis strongly supports the existence of underlying dimensions. Note that we replicated this analysis using different rotation methods (i.e., 'varimax' and 'oblimin') and different cutoff rules (i.e., removing items with communalities below 0.4 instead of 0.2).

We ended up selecting 20 items, based on their loadings (i.e., giving priority to high loadings) and their consistency with the theoretical model (see Table 1). Note that most of the items that loaded in the last iteration of the factor analysis, and that we ultimately removed to shorten the questionnaire, were in fact consistent with this partition (see Supplementary Material). The few counterexamples were all localized in Factor 1, which explained most of the variance in the factor analysis. For example, 'Using my previous knowledge of Video games to fulfill my goals', which loaded on the Experimenting factor, seems to be more related to high-order exploitative goals: we would have expected this item to load onto the Expanding factor (Factor 4).

We then looked at how items clustered and, more importantly, checked whether such clusters were consistent with the theoretical framework.

Factor 1 groups together *items that reflect a preference for experimenting (*i.e.*, exploring low-level action-outcome associations)* such as 'Trying out new ways of using my weapons and tools', 'Inventing new strategies all the time', or 'Discovering new ways to play' (see Fig. 3, bottom left quadrant: "Experimenting").

Factor 2 groups together *items that reflect a preference for discovering (*i.e.*, exploring high-level action-outcome associations)*, such as 'Fulfilling side quests that lead to new information', 'Looking for and completing all the side quests', 'Discovering new places' (see Fig. 3, top left quadrant: "Discovering").

Factor 3 groups together *items that reflect a preference for performing (*i.e.*, exploiting low-level action-outcome associations)*, such as 'Using the best move or combo over and over again', 'Following a predefined order of quest', or 'Doing simple and repetitive tasks' (see Fig. 3**,** bottom right quadrant: Performing).

Finally, **Factor 4** groups together *items that reflect a preference for expanding (*i.e.*, exploiting high-level action-outcome associations)*, such as 'Watching the cinematics that explain the backstory', 'Listening to non-player characters', or 'Relying on my understanding of the story' (see Fig. 3, top right quadrant: "Expanding").

Overall, this Exploratory Factor Analysis is consistent with the theoretical model of preferred gaming actions and goals, derived from the hierarchical model of goal-oriented actions presented earlier (see Fig. 3). The results nevertheless call for two preliminary remarks.

First, two items from Factor 3, namely "Looking for and completing all the sidequests" and "Accumulating collectible items", are not only indicative of an exploratory impulse, but also seem closely tied to *completion*. This sense of completion pertains to the urge to finalize unfinished tasks, such as completing a collection. Intriguingly, while completion may intuitively feel akin to exploitation, it often requires exploration, albeit with a *known outcome*, to be accomplished. This association between completion and exploration is somewhat expected, as it highlights that exploratory behaviors can occasionally overlap with needs that *require* exploration to be satisfied – such as the need for completion. However, whether exploration and completion share common underlying mechanisms or perform analogous functions remains a topic for further investigation. We explore this distinction between exploration with known and unknown outcomes in more detail in the Discussion section.

A second observation concerns the items grouped under Factor 4. At first glance, trying to understand the backstory of a game (e.g., "Watching cinematics that explain the backstory") seems intuitively part of the *exploratory* dimension of gaming behavior. However, we classify these behaviors under the dimension of Expanding, which falls under the *exploitation* category. This is because Factor 4 pertains to the player's engagement with "embedded" content, which can only be exploited with limited agency. This predetermined content precludes players from

Table 1
Results of the Exploratory Factor Analysis of the Gaming Questionnaire (GQ): items spontaneously cluster into 4 dimensions or factors (K = 4), which account for a total of 43 % of the variance in the data. Overall, the factor analysis provided good support for the existence of 4 underlying dimensions in the data. SS loadings, Proportion variance and Cumulative variance indicate said measure for the entire factor analysis (not just the items selected after the analysis).

	1	2	3	4	Comm	Uniq
GQ1 – Trying out new ways of using my weapons or tools	**0.860**	*−0.016*	*−0.099*	*−0.042*	0.64	0.36
GQ2 – Inventing new strategies all the time	**0.854**	*−0.139*	*0.016*	*−0.031*	0.59	0.41
GQ3 – Discovering new ways to play	**0.716**	*0.053*	*−0.088*	*0.066*	0.53	0.47
GQ4 – Experimenting things outside the role of my character	**0.675**	*0.010*	*−0.034*	*0.107*	0.48	0.52
GQ5 – Executing new move or combo all the time	**0.664**	*−0.146*	*0.241*	*−0.008*	0.51	0.49
GQ6 – Fulfilling sidequests that lead to new information	*0.030*	**0.794**	*−0.117*	*0.168*	0.66	0.34
GQ7 – Looking for and completing all the sidequests	*−0.117*	**0.790**	*0.030*	*0.035*	0.55	0.45
GQ8 – Discovering new places	*0.277*	**0.611**	*−0.160*	*0.030*	0.57	0.43
GQ9 – Exploring or discovering new items	*0.317*	**0.577**	*−0.105*	*−0.045*	0.58	0.42
GQ10 – Accumulating collectible items	*−0.085*	**0.493**	*0.251*	*0.008*	0.37	0.63
GQ11 – Using the best move or combo over and over again	*0.111*	*−0.050*	**0.634**	*−0.098*	0.46	0.54
GQ12 – Following a predefined order of quests	*−0.148*	*0.016*	**0.629**	*0.053*	0.33	0.67
GQ13 – Maintaining my strategy no matter what until it works	*0.178*	*−0.238*	**0.618**	*−0.018*	0.37	0.63
GQ14 – Using the same tool or weapon over and over again	*−0.155*	*0.033*	**0.617**	*0.063*	0.32	0.68
GQ15 – Doing simple and repetitive tasks	*−0.223*	*0.027*	**0.559**	*0.093*	0.24	0.76
GQ16 – Watching cinematics that explain the backstory	*0.207*	*−0.022*	*0.229*	**0.772**	0.74	0.26
GQ17 – Skipping the cinematics (reversed)	*0.213*	*0.160*	*0.021*	**0.556**	0.51	0.49
GQ18 – Listening to non-player characters	*0.213*	*0.160*	*0.021*	**0.556**	0.51	0.49
GQ19 – Finding out as many details of the story as possible	*0.226*	*0.236*	*0.113*	**0.486**	0.56	0.44
GQ20 – Relying on my understanding of the story	*0.229*	*0.158*	*0.209*	**0.426**	0.48	0.52
SS loadings	**9.16**	**6.77**	**3.92**	**2.15**		
Proportion variance	**0.18**	**0.13**	**0.08**	**0.04**		
Cumulative variance	**0.18**	**0.31**	**0.39**	**0.43**		

exploring alternative sequences, let alone modifying the narrative and its context. In game cinematics, for example, the player's action is almost systematically suspended: players are mere spectators who, at best, are left with the illusory impression of controlling the narrative sequence, as exemplified in *Metal Gear Solid's* much-discussed final "event scene" [151]. This type of experience mirrors the notion of passive learning in cognitive science, where individuals receive new information without engaging or searching for it, in contrast to active learning, which involves direct participation and interaction with the environment [58].

3.7. *Confirmatory factor analysis*

3.7.1. *Method*

We used confirmatory factor analysis (CFA) to examine the factor structure of the Gaming Questionnaire as presented in Table 1. CFA is a statistical technique that tests whether a set of observed variables can be explained by a proposed underlying structure of latent (unobserved) variables. In our case, the latent variables were the four dimensions of goal-oriented behavior, and the observed variables were the questionnaire items. We fit the CFA model to the data using maximum likelihood estimation and evaluated the model fit using two metrics: the RMSEA and the TLI.

3.7.2. *Results*

The CFA results indicated a moderate fit to the data, with RMSEA = 0.0809 and TLI = 0.848 (see Supplementary Materials for the table of variance). This suggests that all 20 items can be explained by the underlying structure of the latent variables measuring the four dimensions of goal-oriented behavior in Video games (see Fig. 3). We also checked that these fit indicators are still good when we replace 'not applicable' responses by 0, so that we can use this questionnaire without any data imputation. The results show an even better fit to the data, with RMSEA = 0.079 and TLI = 0.83. Note that in the analyses that follow, "not applicable" is replaced by 0, under the assumption that if an individual does not know whether they like a specific type of action in a Video game, chances are they do not like it (otherwise, they would have ended up testing it).

3.8. *Stability of the scale*

Understanding the stability of psychometric scales is crucial for the reliable assessment of psychological constructs. Here, we predict that participants' responses (i.e., their preferences for specific dimensions of Video game experience) are stable over time.

3.8.1. *Method*

To test the stability of participants' responses, we used the test–retest

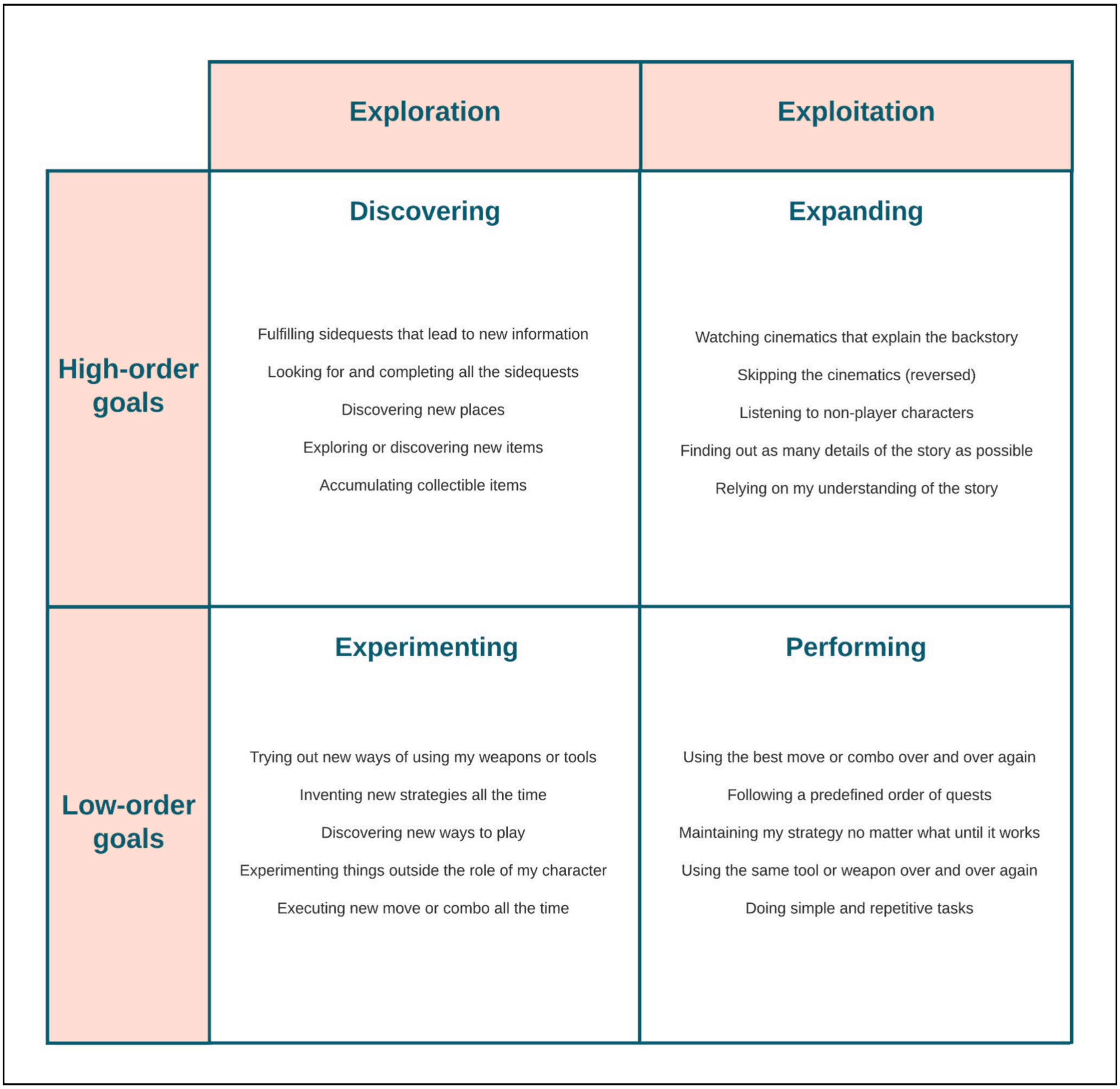

Fig. 3. Final Gaming Questionnaire. The Gaming Questionnaires, with its 20 items, measures scores on 4 dimensions, which are consistent with a hierarchical model of goal-oriented actions: Performing, Experimenting, Expanding, and Discovering. See **Appendix A** for further instruction.

method. This method involves administering the same questionnaire to the same group of participants at two different points in time and comparing responses between the two administrations. The test–retest method allowed us to determine the consistency of responses over time, an important prerequisite when determining the reliability of a new scale. If responses are consistent over time, this suggests that the questionnaire measures a stable set of constructs that are not influenced by temporary factors or random fluctuations.

To administer the questionnaire, we recruited a sample of 350 participants who had previously participated in the first experiment (Time 1), 14 weeks later (Time 2). The participants were asked to complete the 20-item DEEP questionnaire. To compare responses between the two administrations, we calculated the intraclass correlation coefficient (ICC) assessing the agreement between the aggregated scores of the DEEP dimensions at Time 1 and Time 2.

3.8.2. *Results*

The ICC value obtained is 0.73. This value indicates that there is a substantial level of agreement between the scores obtained at Time 1 and Time 2, suggesting that the measures used in the study are stable over time. The result of the F-test was also consistent with this interpretation, as the p-value was close to 0, indicating that there is a significant correlation between the scores obtained at Time 1 and Time 2. We calculated the ICC for each score to compare the stability of each dimension. From highest to lowest stability, we found Expanding (ICC = 0.75), Discovering (ICC = 0.72), Experimenting (ICC = 0.68), and finally Performing (ICC = 0.59).

The fact that high-level dimensions show greater intra-individual stability than low-level dimensions suggests that players' high-level goals in video games (i.e., their desire for Expanding and Discovering) are more stable over time than the specific actions or strategies they implement in these games. This observation is consistent with the idea that, in real life, high-level goals are less likely to be updated and renewed than low-level goals. Just as a person's overarching life goals are likely to be more stable than their everyday actions, a player's high-level motivations are likely to be more stable than their specific in-game actions or strategies. This finding underlines the importance of considering both high-level and low-level dimensions in understanding players' experiences and behaviors in Video games.

3.9. Intermediate discussion

The results from the cluster analysis provide a solid basis for the DEEP (Discovering, Experimenting, Expanding, Performing) model. The DEEP questionnaire, as the analysis demonstrates, is a reliable tool for understanding the variability of gaming preferences, offering a comprehensive framework for the study of players' behaviors.

There are, however, certain limitations to the DEEP model. As mentioned, the Discovering dimension, which encompasses the exploration of new quests, also includes items related to completion. This may seem counterintuitive, as completion usually means the end of discovery (and is negatively correlated to a tolerance to ambiguity, which is nonetheless required by high-level exploration; [74,81]). However, this could be interpreted as the culmination of the discovery process, where the player's understanding of game mechanics is validated by the successful completion of tasks or objectives. The presence of completion-related items here could thus reflect the player's desire for structure, closure, and achievement, which are important aspects of some gamers' experience, and which can only be achieved through systematic high-level exploration (see Dubourg et al., 2022; [110], for experimental evidence of an association between the personality trait 'Openness to experience' and the psychological construct 'Systemizing').

The second point pertains to the Expanding dimension. We pointed out earlier that this dimension is more closely aligned with exploitation behaviors than with exploration behaviors. A second point is that the model does not really account for high-level *strategic* actions. While the Expanding dimension of the DEEP questionnaire encompasses the achievement of high order goals through the exploitation of narrative information, its five items do not explicitly account for the exploitation of *planned* strategies. This is an important aspect of gameplay, particularly in strategy-based games where players are required to devise complex abstract plans to achieve long term objectives. The absence of this element in the questionnaire suggests a potential area for improvement.

While these questions warrant further investigation, they also highlight the DEEP model's potential to evolve and adapt to the multifaceted nature of players' motivations and behaviors. Future studies could explore these aspects, refining the DEEP model and potentially developing a 'longer' questionnaire that would encompass a wider range of actions. Here, our focus remains on studying the predictive power, psychological underpinnings, and hierarchical structure of the DEEP dimensions as they currently stand. In the following section, we explore the hierarchical nature of DEEP dimensions, with the aim not only of producing an external validation of the questionnaire, but also of validating a new methodology based on AI annotation.

4. Study 2: The hierarchical structure of the DEEP model

The DEEP (Discovering, Experimenting, Expanding, Performing) model provides a comprehensive framework for understanding player behaviors in Video games. The relationship between high-level and low-level goals within this model remains an area of interest. In this second study, we hypothesize that Video games should exhibit a "nested" pattern, consistent with the hierarchical structure of goal-directed actions (on cultural nestedness, see [105]). More specifically, we predict that games that help achieve high-level goals (Discovering or Expanding) also help achieve low-level goals (Experimenting or Performing), but not necessarily vice versa (i.e., games implementing low-level goals do not necessarily allow you to achieve high-level goals).

This nestedness pattern is intuitive when considering the nature of gameplay. High-level goals, such as saving a kingdom or solving a complex mystery, often require the completion of a series of low-level goals, such as mastering a combat system or solving puzzles. Conversely, games that primarily focus on low-level goals, such as a simple puzzle game, do not necessarily require the completion of high-level goals. Take Zelda as an example: you can achieve high-order objectives, such as saving Hyrule, which is an abstract, long-term quest that involves Discovering and Expanding (e.g., wandering around the map, learning more about non-player characters); but to do so, you also need to accomplish lower-level objectives, such as using weapons or solving riddles, which are concrete, short-terms goals that involve Experimenting and Performing (e.g., fighting moblins or training in the use of Runes, such as the Magnesis).

The prediction is therefore as follows: there should be many video games that allow the achievement of low-level goals without allowing the achievement of high-level goals (e.g., Tetris), while there should be fewer Video games that only allow the achievement of high-level goals – the reason being that achieving high-level objectives should generally require the fulfillment of multiple low-level sub-objectives distributed throughout the hierarchy.

The following analysis aims to test this hypothesis in order to provide a nuanced understanding of the nestedness pattern in Video games. In doing so, we hope to shed light on the hierarchical structure of both the DEEP dimensions and the underlying cognitive model of goal-directed actions. Design, procedure, and predictions were all pre-registered (https://osf.io/jgrzt).

4.1. Material

For this study, we used the 'Video Game Sales' dataset, which includes titles and metadata (e.g., release date, platform) of best-selling Video games (sales over 100,000 copies) for 16,598 video games from various platforms, released between 1980 and 2016. This dataset provides a large and diverse sample of Video games, allowing us to investigate the nestedness pattern across a wide range of gameplay experiences.

4.2. Automatic annotation

This analysis requires evaluating all the video games from this dataset along the DEEP dimensions. However, traditional methods relying on participant ratings and online metadata have limitations. Online metadata, for example, can be informative (e.g., [44]) but for video games it poses significant challenges. The scarcity and inconsistency of available metadata often make it unreliable for a comprehensive rating of existing games. In addition, the absence of standardized formats and the varying levels of detail in the description of game mechanics make it difficult to collect homogeneous data across different games. These limitations prevent the use of online metadata as a primary source for video game rating.

Participant-based ratings also present a challenge in this context, as they require finding individuals who have played a large number of games with a wide variety of game mechanics. In addition, this approach may yield biased or unreliable results due to varying subjective preferences. Obtaining objective and consistent ratings would require providing multiple annotations by multiple coders for each game, to verify agreement between raters. This method would require recruiting tens of thousands of people – a task impossible to achieve as it stands.

To evaluate video games according to the DEEP (Discovering, Experimenting, Expanding, Performing) framework, we therefore turned to an alternative method, based on GPT, a state-of-the-art Large Language Model (Brown et al., 2020). The implementation of GPT as an alternative annotation method offers several advantages (e.g., [123,128,168]). With its extensive training on a wide range of textual sources, including information related to Video games from various websites (e.g., reviews, walkthroughs, strategy guides, forums, discussions between gamers, news articles), GPT has an extensive knowledge base of video games released before 2021. This enables the model to provide detailed and accurate answers concerning gameplay elements, narratives, and other relevant features. By prompting the model with specific inquiries, namely the characteristics associated with each DEEP dimension, it can retrieve and integrate relevant information to generate informed ratings (see [43], for a Method article about this Automatic Annotation process).

We took several precautions to ensure the reliability and consistency of the ratings. These include cross-validation with multiple prompts, careful consideration of context, and critical evaluation of model responses (see Appendix B for the outcomes of AI annotation for four Video games, and a prompt that can be used to annotate any Video game on ChatGPT, by just mentioning the title). Next, we will test that the dimensions correlate with expected genres as specified in the original dataset.

Here are the prompts that we used to rate Video games with GPT:

For Discovering:

Discovering (High-level Exploration): Discovering is about using novel and innovative actions or strategies to achieve abstract goals. Discovering involves actively exploring the game world, uncovering hidden secrets, and engaging in non-linear gameplay elements. It includes the ability to undertake side quests or optional objectives that offer new insights, items, or areas to explore. You will rate a video game on a scale of 0 to 100 on this dimension. This score will reflect how well the game aligns with the characteristics and potential of this dimension. Give a single number, without text. The video game is:

For Experimenting:

Experimenting (Low-level Exploration): Experimenting is about using novel and innovative actions or strategies to achieve concrete goals. Experimenting focuses on the player's ability to innovate and try out different strategies, approaches or play styles within the game's mechanics. This includes experimenting with different weapons, abilities, or tools to meet challenges or discover unique solutions. You will rate a video game on a scale of 0 to 100 on this dimension. This score will reflect how well the game aligns with the characteristics and potential of this dimension. Give a single number, without text. The bideo game is:

For Expanding:

Expanding (High-level Exploitation): Expanding is about using familiar, mastered actions or strategies to achieve abstract goals. Expanding emphasizes player engagement with the game's lore, storylines, and characters. This involves delving deeper into the narrative, interacting with non-player characters, and seeking out additional details or lore-rich content. You will rate a video game on a scale of 0 to 100 on this dimension. This score will reflect how well the game aligns with the characteristics and potential of this dimension. Give a single number, without text. The video game is:

For Performing:

Performing (Low-level Exploitation): Performing is about using familiar, mastered actions or strategies to achieve concrete goals. Performing focuses on the player's mastery of game mechanics and execution of well-practiced strategies to achieve specific goals or tasks. This involves effective use of abilities, precise timing, or skill-based gameplay elements. You will rate a video game on a scale of 0 to 100 on this dimension. This score will reflect how well the game aligns with the characteristics and potential of this dimension. Give a single number, without text. The video game is:

We used an R script to prompt GPT to rate the 16,598 video games of the dataset along the DEEP dimensions. The prompts focus on the characteristics associated with each dimension, and GPT provides a score on a scale of 0 to 100. This score reflects how well the game aligns with the characteristics and potential of the dimension. The prompts are used in a loop to extract scores for multiple games using the GPT API.

4.3. Prediction and statistical analysis

To test the nestedness structure in video games, we created two new binary variables for each game based on the DEEP model scores provided by GPT: one for high-level goals and one for low-level goals. The 'High Level' variable is equal to 1 if the average score of the high-level dimensions (Discovering and Expanding) for a game is greater than 50, and 0 otherwise. The 'low level' variable is equal to 1 if the average score of the low-level dimensions (Experimenting and Performing) for a game is greater than 50, and 0 otherwise. Basically, the High-Level variable and the Low-Level variable measure, for any given game, whether it allows the completion of high-level goals and low-level goals, respectively (independent of the exploration dimension).

We then set aside video games that allow both types of goals, or none at all, and kept only the other types of video games (see Fig. 5**.A.**). The first combinations are obviously nested: they enable goals to be achieved at both levels of the hierarchy, or at none (see, for example, video games where you never interact with the game, such as *Wii Fit*, which GPT rightly annotates as low on all four dimensions). Next, we created a 'nestedness compatibility' variable to indicate the Video game's compatibility with the nestedness pattern. It is defined as 1 if the video game helps achieve low-level goals but not high-level goals, and 0 otherwise. Video games that allow the completion of high-level goals but not low-level goals are incompatible with the nestedness pattern.

We predict that, among those games that allow only one type of goal to be accomplished, the proportion of nestedness-compatible video games will be significantly greater than 0.5, indicating that a majority of video games are compatible with the hierarchical structure of goal-directed actions. A one-sample proportion test will be performed to quantify the proportion of nestedness-compatible Video games among games that allow only one type of goal to be fulfilled. This test will determine whether the observed proportion differs significantly from the null hypothesis proportion of 0.5.

4.4. Results

4.4.1. Consistency check of GPT annotations

The consistency of the annotation was evaluated by performing a series of linear regression analyses. The four dependent variables in these analyses were the ratings produced by GPT on the four DEEP dimensions: Discovering, Performing, Expanding, and Experimenting. The independent variable was the genre of the video game, with the Action genre serving as the reference category. We added the year of release of the video games as a fixed effect in the model. All four models showed a significant main effect of genres (see Fig. 4). These models clearly show that the DEEP dimensions are not uniformly distributed across all game genres.

The Platform and Role-Playing genres were positively associated with Discovering ($\beta = 2.86$, *p-value* $= 0.003$ and $\beta = 17.53$, $p < 0.001$), suggesting that these genres, known for their exploration and narrative depth, foster a greater sense of discovery than Action games. Conversely, genres such as Fighting, Puzzle, Racing, Simulation, and Sports were negatively associated with Discovering ($\beta = -12.01$, $p < 0.001$; $\beta = -11.06$, *p-value* < 0.001; $\beta = -18.93$, $p < 0.001$; $\beta = -28.72$, $p < 0.001$). This negative association is consistent as these genres often focus on specific gameplay mechanics, thus limiting the scope for discovery.

The Role-Playing and Strategy genres were positively associated with the Expanding dimension ($\beta = 22.15$, $p < 0.001$ and $\beta = 4.73$, $p < 0.001$), indicating that these genres, known for their expansive worlds and complex systems, promote a greater sense of expansion than Action games. In contrast, genres such as Platform, Shooter, Simulation, and Sports, for instance, were negatively associated with Expanding ($\beta = -4.39$, $p < 0.001$; $\beta = -0.86$, $p < 0.001$; $\beta = -10.98$, $p < 0.001$; $\beta = -26.26$, $p < 0.001$), consistent with the observation that these genres often have more constrained worlds.

The Role-Playing, Shooter, and Strategy genres were positively

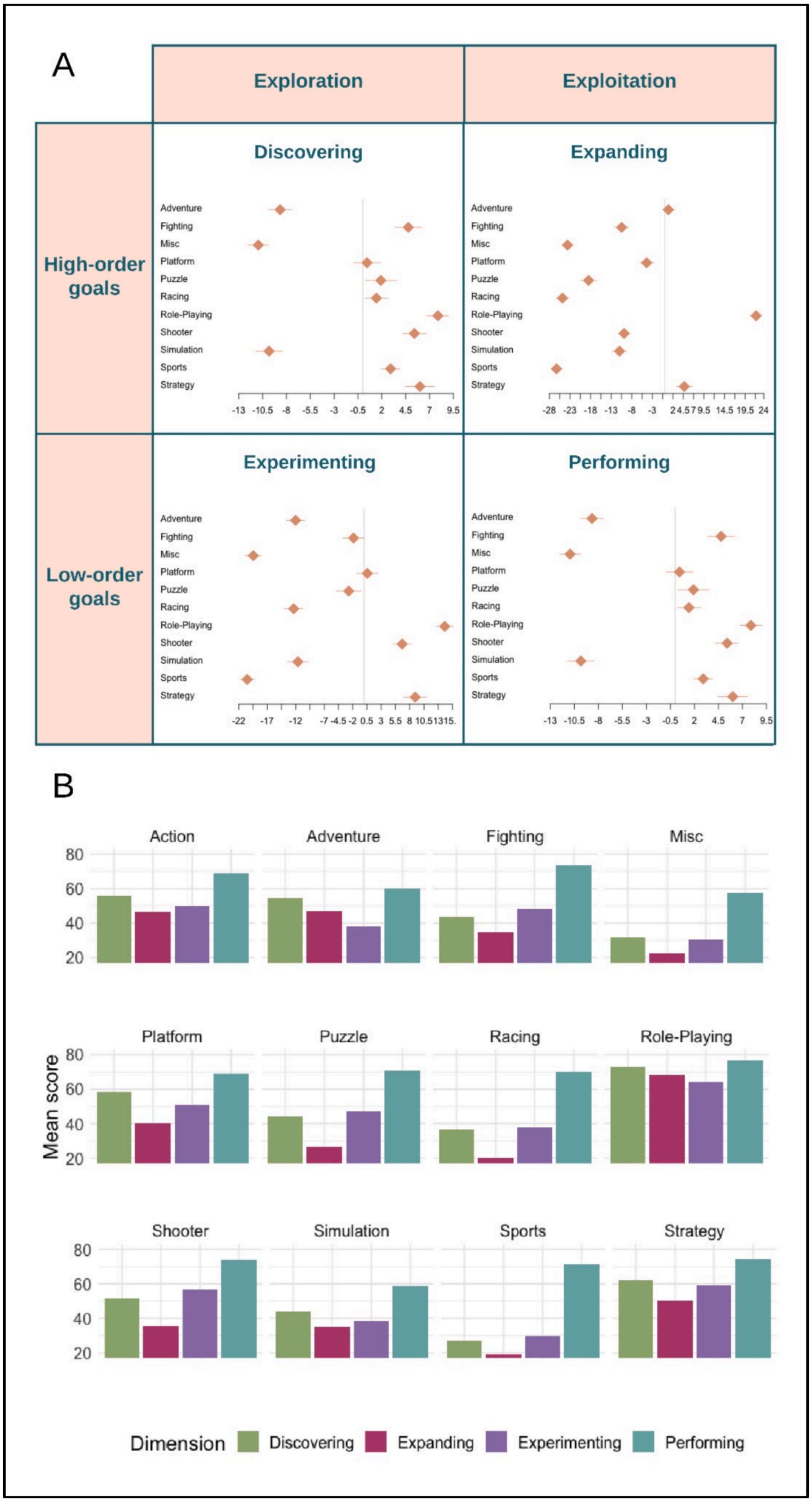

Fig. 4. A. Forest plot of beta coefficients for genre categories in the four models (i.e., one model per dimension), with the DEEP score of the video games on this dimension as the outcome variable, and the genre categories as the explanatory variable. The reference category is the Action genre. Coefficients to the left of the vertical line mean that the DEEP score is negatively associated with the genre (the higher the score, the *weaker* the preference for that genre should be), while coefficients to the right mean that the DEEP score is positively associated with the genre (the higher the score, the *stronger* the preference for that genre). Coefficients crossing the vertical line are not significantly different from 0. **B.** Box plot of the mean DEEP scores by genre.

associated with the Experimenting dimension ($\beta = 15.16$, $p < 0.001$; $\beta = 6.68$, $p < 0.001$; $\beta = 6.97$, $p < 0.001$), suggesting that these genres are more conducive to experimentation than Action games. Such associations were expected, as these genres often provide a variety of tools and concrete strategies for players to experiment with. Conversely, the Puzzle, Racing, and Simulation genres were negatively associated with Experimenting ($\beta = -2.69$, $p = 0.016$; $\beta = -12.36$, $p < 0.001$; $\beta = -11.62$, $p < 0.001$). These negative associations align with the intuition that these genres often have more defined rules or mechanics and leave less room for experimentation.

Finally, Fighting, Role-Playing, Shooter, Puzzle, and Strategy genres showed a positive association with the Performing dimension ($\beta = 4.78$, $p < 0.001$; $\beta = 7.79$, $p < 0.001$; $\beta = 5.40$, $p < .001$; $\beta = 1.90$, $p = 0.02$; $\beta = 6.00$, $p < 0.001$) Such associations suggest that these genres, which often require concrete actions and controlled execution, are conducive to higher levels of performance than Action games. On the other hand, the Adventure and Simulation genres were negatively associated with Performing ($\beta = -8.66$, $p < 0.001$ and $\beta = -0.82$, $p < 0.001$), consistent with our understanding that these genres often prioritize exploration or narrative over performance-based gameplay.

In summary, the results of the linear regression analyses indicate that automatic annotation by GPT is consistent across different video game genres.

4.4.2. Nestedness analysis

We then tested our pre-registered prediction that, among our sample of interest (video games allowing only high-level goals or only low-level goals), there are significantly more video games exhibiting a nested pattern (video games allowing the achievement of low-level goals, but not high-level goals) than non-nested (video games allowing the achievement of high-level goals, but not low-level goals).

The results of the one-sample proportions test were highly significant ($X^2 = 2884.3$, $df = 1$, $p < 0.001$), providing strong evidence to reject the null hypothesis (i.e., that the proportion of video games with nestedness compatibility equal to 0.5). The 95 % confidence interval for the proportion of Video games with nestedness compatibility was (0.89, 1), indicating that at least 89 % of all Video games are compatible with the nested structure assumed by the DEEP model. The sample estimate of the proportion was 0.9, indicating that 9 out of 10 games in the sample are compatible with the nested structure.

4.5. Intermediate discussion

This result strongly supports the nested structure of the DEEP model in the context of Video games. As expected, the DEEP dimensions are not independent of each other, but are organized hierarchically. This hierarchical organization suggests that the model's dimensions do not simply represent different aspects of gameplay, but reflect a deeper structure in the way goals and actions are represented in video games. This structure, we believe, mirrors the hierarchical organization of goal-directed actions in agents, with low-level goals (Performing and Experimenting) serving as the basis for higher-level goals (Discovering and Expanding).

5. Study 3: The predictive power of the DEEP dimensions

This section aims to investigate the predictive power of the DEEP dimensions. Our hypothesis is that participants' scores on each DEEP dimension should predict which video games they prefer based on the DEEP scores of those games. In other words, we expect participants' DEEP scores, as assessed by the DEEP questionnaire only, to correlate with self-reported Video game DEEP scores, as assessed by GPT only. This hypothesis stems from the idea that players are naturally drawn to games that align with their preferred modes of engagement, as represented by the DEEP dimensions. This echoes the view of Williams et al. [160] who suggest that "it would be both theoretically rich and practically valuable to determine which game mechanics satisfy which motivations (…) Such knowledge", they add, "would help game makers make more appealing games, of course, but it would also help us leverage game mechanics into other contexts such as educational games or collaborative virtual workspaces".

By testing our hypothesis, we aim to demonstrate that the DEEP questionnaire is not only a reliable measure of players' game preferences, but also a powerful tool for predicting player-game compatibility. The results of this study could have significant implications for game design and player experience research, providing a robust, theory-based approach to understanding and predicting game-player interactions. It also comes as a further check on the external validity of the AI-annotation method used in this work. The design, procedure, and predictions were all pre-registered (https://osf.io/jgrzt).

5.1. Participants

Our sample size was determined by a power analysis, with a significance level set at 0.05 and a desired power set at 90 %. We anticipate a small effect size, a consequence of the nested structure of video games in which people can enjoy high-level goals while playing video games that promote both the high- and low-level dimensions of the DEEP model. With a maximum of five predictors in our models (see Study 4), the power analysis indicates that a sample size of at least 514 is required to confidently detect small effect sizes. We recruited 1,000 participants from the United States, so as to be able to detect such small effects, even with the added complexity of random variables and potential interactions. Recruitment was carried out through Prolific Academic, and all participants were paid on completion of the study.

In line with our pre-registered exclusion criteria, 7 participants were rejected due to failed attention check, 1 because they answered "Don't apply" to more than 50 % of the DEEP questionnaire questions, and 9 because they did not list any video games. We further removed 8 participants who reported being 1 year old. We carried out the analyses with 961 participants (479 males, 456 females, 22 non-binary/third gender, 4 'prefer not to say'; $M_{age} = 36.2$, $SD_{age} = 12.4$). Participants reported playing an average of 13 Video games in the past year ($SD_{n\_vg} = 11.3$) and playing an average of 13 h per week ($SD_{h\_vg} = 11.01$). Note that the average number of video games and the average number of hours spent playing reported here are very similar to those in Study 1.

5.2. Design and procedure

Participants were asked to complete the DEEP questionnaire as developed in Study 1 (see Appendix A for the full questionnaire). They were then asked to list up to 10 video games they had played recently:

Please now list the titles of video games you have dedicated substantial time to in your recent gaming experiences. Include all types of Video games from all platforms (including mobile games). Take your time – this is the last part of the study. You can list a maximum of 10 video games. Please list as many as possible.

We decided not to ask participants what their *preferred* video games were, as we felt that with such wording, they might mention old video games they had enjoyed in the past but would no longer enjoy today, which would have prevented us from capturing their *current* preference, which is the measure of interest here. Note that we expect preferred video games to change with age as a result of developmental changes in preferences. The wording of the question – "Have you spent a lot of time on your recent gaming experiences?" – assumes that gamers rarely invest a lot of time in games they dislike.

Participants listed a total of 5,791 Video games (3,229 distinct ones). To assess the DEEP dimensions of these video games, we used the same automatic annotation method as in the previous study (see **4.2.**). Note that, in the same experiment, other psychological questionnaires relevant to our next study were asked of the participants. These are described in detail in the next section.

5.3. Prediction and statistical analysis

The statistical analysis for this study is designed to test our hypothesis that participants' DEEP scores can predict the Video games they play, based on the DEEP scores of those games.

A linear mixed-effects model was used for this analysis. The predictor variables in this model were the DEEP scores of the participants, which we obtained from the 20-item DEEP questionnaire. The outcome variables were the DEEP scores of the participants' mentioned Video games (as annotated by GPT, see **4.2.**). We have accounted for potential variability between different Video games and different DEEP dimensions by including these variables as random variables in the model. We predicted a significant and positive regression coefficient between the DEEP scores of the participants (as measured by the DEEP questionnaire) and the DEEP scores of the participants' mentioned Video games (as assessed by GPT).

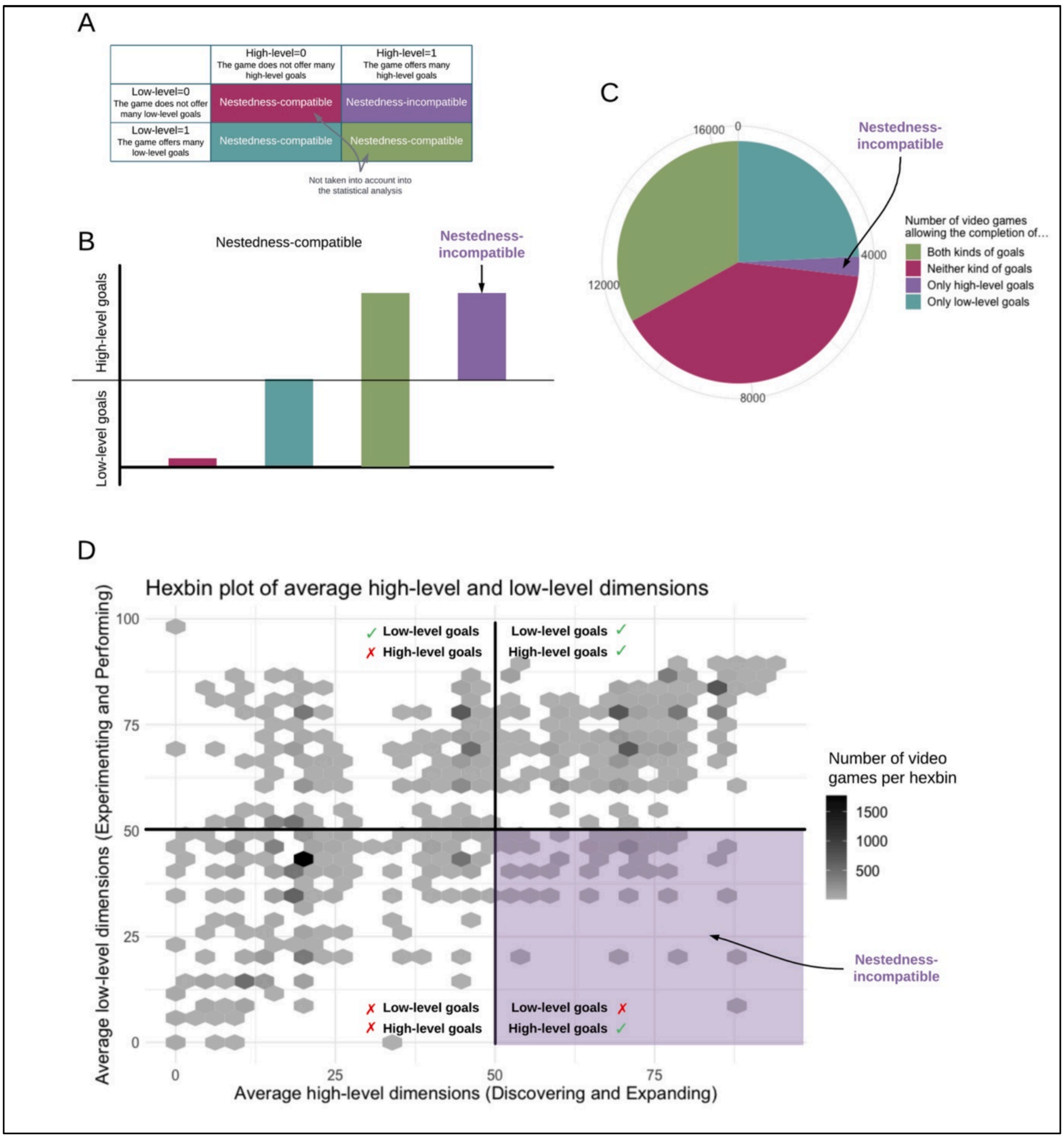

Fig. 5. A. A table of all possible goal combinations. The only combination not compatible with nestedness is shown in purple. In the statistical analysis, we removed two categories (as pre-registered): the red and green combinations, which are trivially nested. **B. Schematic representation of the four possible combinations of high-level and low-level goals.** To the left of the middle vertical line, the bars represent games that do not allow either low-level or high-level goals to be achieved – in other words, games that score very low on all dimensions (red bar), that allow only low-level goals (blue bar) or that allow both kinds of goals to be achieved (green bar). To the right of the same line, the purple bar represents games that are incompatible with nestedness, allowing only high-level objectives to be met, but not low-level ones. **C. Number of video games in each of these categories** (N = 16,598 video games). As expected, we see a low number of games that show non-nested patterns. **D. Graphical representation of the nestedness pattern** (N = 16,598 video games). Again, we see that there are few video games whose scores are incompatible with the expected nestedness pattern (bottom right quadrant, colored in purple). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

5.4. Results

The model revealed a significant positive relationship between the participant's score and the Video game score on the DEEP dimensions ($\beta = 1.9152$, $p < 0.001$): as the participant's score increases, so does the video game score (see Fig. 6**.A.**). Although this was not pre-registered, we decided to decompose the effect of each dimension to determine whether all were indeed predictive. We ran four different models, with video game DEEP scores as the dependent variable and participants' DEEP scores as the independent variable.

Interestingly, the Performing dimension was not predictive of the participants' scores ($\beta = -0.08$, $p = 0.62$*),* which can be explained by the fact that Performing is the most basic dimension and, by virtue of the nested structure of video games, *all* Video games tend to score high on this dimension. This is visually evident in the plot shown in Fig. 6**.B.** As mentioned, this result is consistent with the notion of nestedness, which suggests that high-level dimensions are more discriminating than low-level dimensions and, consequently, more predictive. This is rather intuitive: to be able to explore, expand or experiment, one has to exploit low-level associations between actions and goals. In other words, the games preferred by players who score *low* on Performing (because they do not like "Doing simple or repetitive tasks", for instance) are high-level games; yet these games score high on *both* high-level and low-level dimensions, by virtue of the nestedness principle. Thus, participants who score low on Performing prefer high-level games which also score high on the Performing dimension, because of the low variance in Performing scores across games.

All three other dimensions were predictive of the participants' scores (for Experimenting: $\beta = 3.2$, $p < 0.001$; for Expanding, $\beta = 6$, $p < 0.001$; for Discovering, $\beta = 5.8$, $p < 0.001$). Thus, for example, a 1-point increase in the 8-point Expanding sub-scale of the DEEP questionnaire, as answered by a given participant, indicates a 6-point increase in the 100-point Expanding scores of the video games they report (as measured through the GPT-annotation method).

5.5. Exploratory analyses

We also pre-registered a research question aimed at determining whether certain DEEP dimensions are characteristic of hardcore gamers. To do this, we examined which DEEP dimensions best predict the *number* of games played and the *time* spent playing, as reported by the participants themselves.

First, we examined the predictive value of the four DEEP dimensions, as assessed by the DEEP questionnaire, on the reported number of Video games played by participants. The analysis revealed that the Discovering and Experimenting dimensions were significant predictors of the number of video games played ($p < 0.001$; $p = 0.0029$; see Fig. 7): individuals with high Discovering and Experimenting scores are likely to be drawn to the novelty and variety offered by different games, and to seek out new experiences and challenges. The Expanding dimension did not significantly predict the number of video games played. Finally, the Performing dimension was *negatively* associated with the number of video games played ($p = 0.0167$). This result suggests that participants who focus primarily on the achievement of low-level goals may actually engage with *fewer* games. One possible explanation for this effect is that people attracted by the Performing dimension devote their time and effort to mastering a few selected games, rather than spreading their attention over a wider variety of games. Taken together, these results are consistent with the DEEP model's exploration–exploitation gradient: individuals who play the greatest number of games are also those who score highest on the *exploration* dimensions (Experimenting, Discovering).

In a parallel analysis, we examined the predictive value of the four DEEP dimensions on the number of hours per week participants report spending playing Video games. The Discovering and Experimenting dimensions were again significant predictors: for each unit increase in the Discovering score, the reported number of hours of play per week increased by around 0.86 h (*p-value* $= 0.033$). Similarly, each unit increase in the Experimenting score corresponded to an increase of around 1.54 h per week (*p-value* < 0.001). These results support the idea that participants who are more prone towards discovery, let alone experimentation, tend to spend more time engaging with Video games. The Expanding and Performing dimensions did not, however, significantly predict the number of hours played per week. This suggests that the drive to expand one's knowledge of the game world, or a focus on performance, does not necessarily translate into more time spent playing.

5.6. Intermediate discussion

The results of our analyses demonstrate the predictive power of the DEEP dimensions for understanding player preferences and behaviors in the context of Video games. The DEEP dimensions – namely Discovering, Experimenting, Expanding, and Performing – were found to be significant predictors of the types of video games players prefer, the number of video games they play and the amount of time they spend playing. In summary, players who scored high on the Discovering and Experimenting dimensions were more likely to prefer games that offer a variety of experiences and opportunities for exploration, and they also played more games and spent more time playing. Conversely, those who scored high on the Performing dimension played fewer games and spent less time playing, which may reflect a focus on mastering a few selected games. Finally, we found that, as predicted, participants' scores on the DEEP questionnaire and the DEEP scores of their favorite video games were correlated (except for Performing, when broken down by dimension), further validating both the DEEP questionnaire (derived from **Study 1**) and the AI-annotation method (proposed in **Study 2**). These findings not only contribute to our understanding of player preferences, but also have potential implications for game design and player engagement strategies.

6. Study 4: The psychological underpinnings of the DEEP dimensions

Having established the DEEP dimensions in our previous studies, we have identified a clear structure in gaming preferences. We have seen how players gravitate towards different aspects of gameplay, from the thrill of discovery to the satisfaction of performance. Yet, the question remains: what drives these preferences? In Study 4, we aim to delve into the psychological and socio-demographic factors that influence these preferences. What personal or societal factors lead a player to prefer exploration over expansion, or performance over experimentation, for instance? By exploring these influences, we can better understand not just how gaming preferences are structured, but why they are structured that way. A better characterization of the factors behind DEEP scores could provide valuable insights for game design, enabling more targeted and effective approaches that respond to the diversity of player preferences. The design, procedure, and predictions were all pre-registered (https://osf.io/jgrzt).

6.1. Design and procedure

This study is based on data collected during the same experiment as Study 3. Following the DEEP questionnaire, participants were also asked to complete the following scales:

Big Five Inventory-2 [144]: This inventory measures the five main personality dimensions – Openness, Conscientiousness, Extraversion, Agreeableness, and Neuroticism. Each of these dimensions captures a set of related personality characteristics [96,101,111,139]; see [163] on the stability of such traits that among 1,039 experimental studies on the variability of human psychology, between 71 and 83 % are in fact associated with the Big Five; see also [5], for a study showing). On a 5-

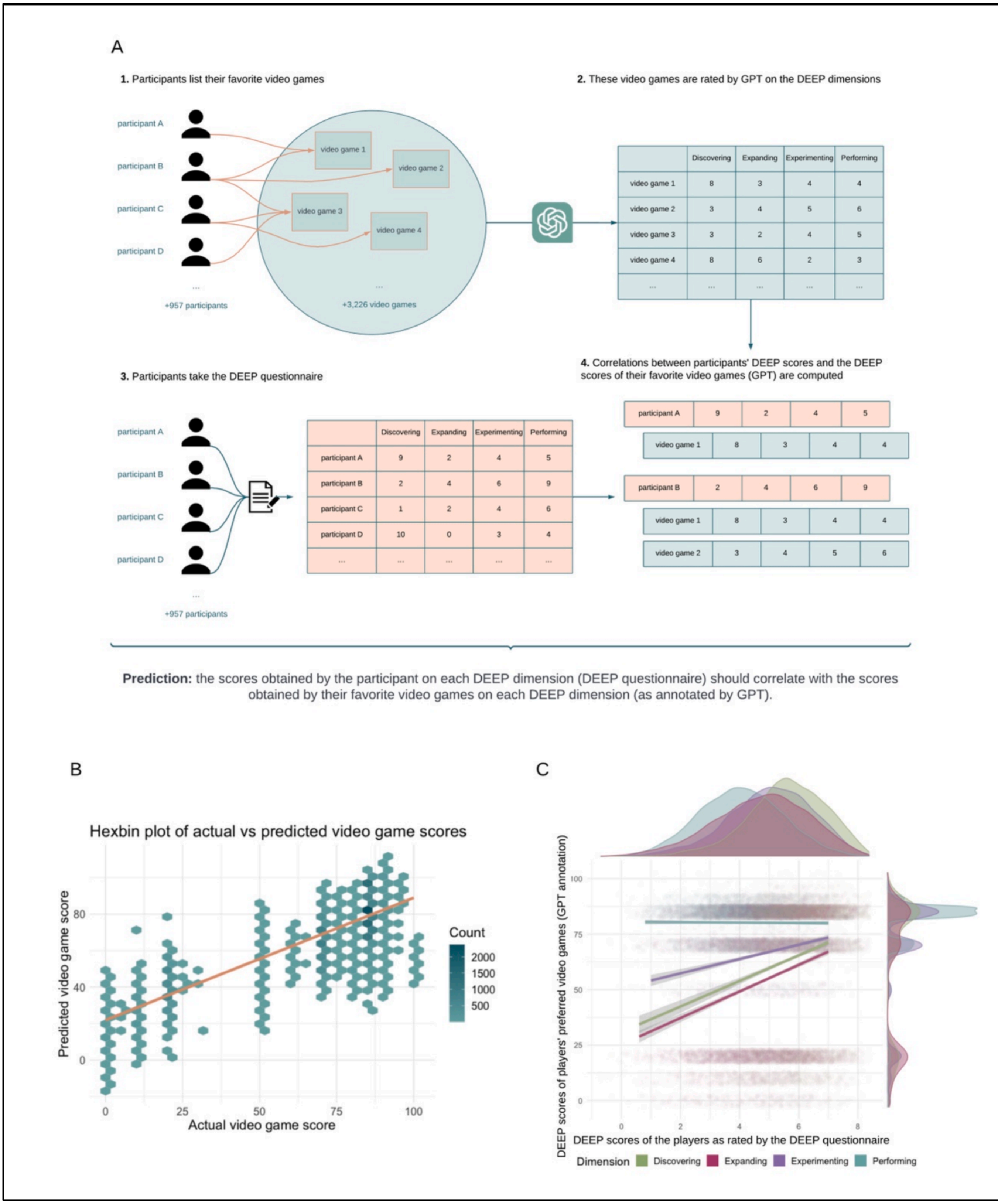

Fig. 6. A. Method. B. Correlation between the actual DEEP scores of players' preferred video games and the predicted DEEP scores, based on their responses to the DEEP questionnaire. In a nutshell, the correlation tests whether the DEEP scores of a player can predict their preferred video games and, conversely, whether their preferred video games allow to infer their responses to the questionnaire. **C. Correlations between participants' scores (DEEP questionnaire: 0–8) and the scores of their favorite video games (ChatGPT annotation: 0–100) for each dimension.** Density plots have been incorporated to illustrate the data distribution for each dimension. Note that the lack of significance of the regression on the Performing dimension is primarily due to the fact that most games score high on this dimension, resulting in low variance in game scores on this dimension.

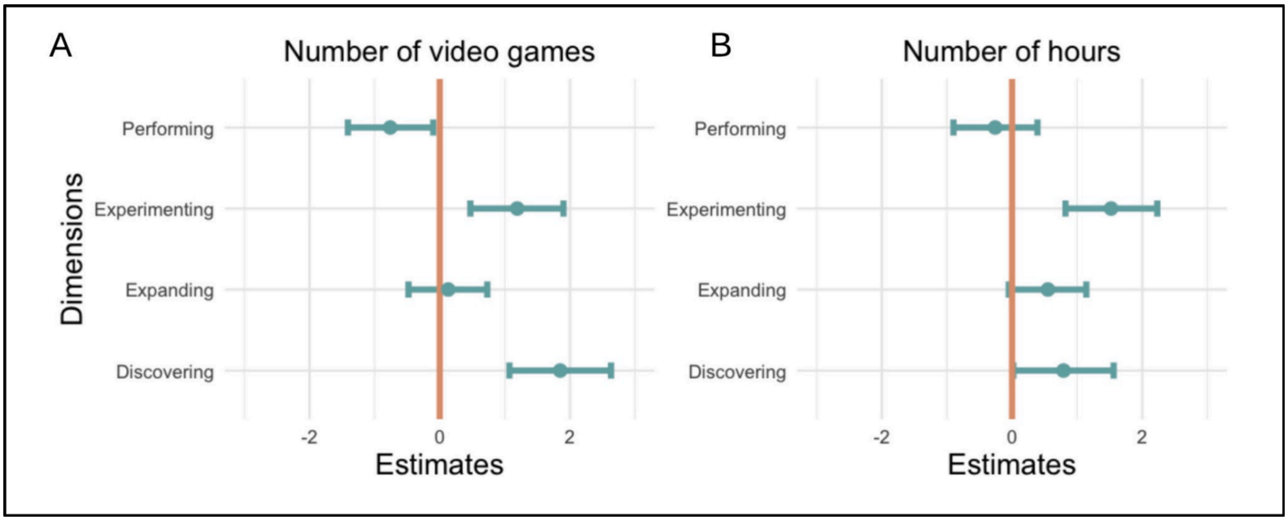

Fig. 7. **A.** Forest plot of beta coefficients estimated by the model, with the reported number of video games played in the past year as the outcome variable, and the four DEEP dimensions measured with the DEEP questionnaire as explanatory variables. **B.** Forest plot of beta coefficients estimated by the model, with the reported number of hours spent playing per week as the outcome variable, and the four DEEP dimensions measured using the DEEP questionnaire as explanatory variables. Coefficients to the right of the vertical line mean that the number of video games played, or hours spent playing, is positively associated with the DEEP dimension (the higher the score on this dimension, the *higher* the number of games played and/or hours spent playing), whereas the coefficients on the right mean that the score on the number of games played, or hours spent playing, is negatively associated with the dimension (the higher the score on this dimension, the *lower* the number of games played and the number of hours spent playing).

point scale, participants are asked to report whether they agree with 30 statements such as 'I am someone who tends to be quiet' or 'I am someone who has little interest in abstract ideas'. For each participant, 5 scores are calculated for each personality dimension.

Behavioral Identification Form [156]: This form measures the level of abstraction at which individuals identify actions. The Behavioral Identification Form (BIF) can provide insights into whether individuals tend to focus on the details of *how* actions are performed (concrete level of identification), or the broader *goals* that the actions are intended to achieve (abstract level of identification). Participants are presented with 25 behaviors, one after the other (e.g., 'Reading', 'Cleaning the house', 'Making a list'). After each behavior, two ways of identifying the behavior are proposed (e.g., for 'Reading', either 'Following lines' or 'Gaining knowledge'). Participants are asked to choose the identification they feel best describes the behavior presented. For each participant, a level of action identification is then measured by calculating the number of times they choose the abstract option. The higher the BIF score, the more people identify their actions at an abstract level.

Five-dimensional curiosity-scale [81]: This scale measures different aspects of curiosity, including Joyous Exploration, Deprivation Sensitivity, Stress Tolerance, Social Curiosity, and Thrill-Seeking. These dimensions reflect the various ways in which curiosity can manifest itself, from the joy of learning new things to the thrill of taking risks. On a 7-point scale, participants were asked to indicate how accurately 25 statements described them (e.g., 'I seek out situations where it is likely that I will have to think in depth about something').

Socio-demographics: We also collected socio-demographic information, including gender, age, and socio-economic status (childhood and current, as used in, e.g., [57,148]). Socio-economic status can provide insights into the social and economic environments in which individuals were raised and currently live, which may influence their gameplay preferences.

6.2. Predictions and statistical analyses

6.2.1. Prediction 1

The Experimenting and Discovering dimensions, which involve exploring new associations at different levels of the goal hierarchy, should be associated with the personality trait Openness (people with higher Openness scores should score higher on these dimensions), age (younger people should score higher on these dimensions) and socio-economic status (people with higher socio-economic status should score higher on these dimensions).

In the personality psychology literature, variation in how individuals deal with the exploration–exploitation tradeoff is reflected by the personality trait Openness to experience, which is one of the Big Five traits related to individuals' curiosity and creativity [37,100,28]. Converging experimental evidence have shown that individuals' preference for exploration (as measured, for example, using the Curiosity and Exploration Inventory scale; [80] correlates with the Big Five trait of Openness [44,74], although it does not correlate with information-seeking tasks ([75].

Developmental psychology literature shows that children are generally more exploratory. An evolutionary reason for this adaptive "developmental division of labor" [16,53,79] is that costs associated with exploration (e.g., resource shortage risk) are outweighed by parental caregiving investments [35,52]. In the laboratory, children are more explorative than adults in foraging tasks [98,99,146], in bandit tasks [147], in explanation-seeking tasks [92,93], in search tasks [27], in decision-making tasks [13,14], in problem-solving tasks [34], in causal-learning tasks [54,95], and in change-detection and visual search tasks [125].

In the behavioral ecology literature, an influential theory postulates that exploratory preferences may vary according to an individual's local ecology, as exploration would have been most adaptive in more affluent environments during our evolutionary history [9,48,69]. In unsafe and deprived ecologies, exploration is very risky, because if exploration does not pay off, one is left with nothing – an effect known as "collection risks". Additionally, the information collected while exploring is beneficial in the long-term, making exploration more adaptive for individuals who discount less the future [137,161]; see also: [122]. The behavioral effect of the local ecological cues on exploratory preferences, curiosity, and spatial search strategies [129] is observed in a wide range of species, from honeybees to parrots to orangutans [10,19,32,51,82,104,134,157]. In humans, there is empirical evidence of such associations between affluence (at both the individual and country level) and exploration or openness to change and novelty [44;71;72,86,103,116,167].

To test this prediction, two regression models were run, with participants' Experimenting and Discovering scores as dependent variables, and participants' Openness score, age, childhood socio-economic status and current socio-economic status as independent variables. In both models, we expected all 4 variables to be significant and positive.

6.2.2. Prediction 2

The Performing and Expanding dimensions, which involve achieving goals at different levels of the goal hierarchy, should be associated with the personality trait Conscientiousness, whose one of the core facets is striving for (goal) achievement.

In the personality psychology literature, Conscientiousness is associated with goal-directed behavior, persistence, rule abiding, decisiveness, and a preference for planned rather than spontaneous behavior [101,132,133]. Individuals with a high level of Conscientiousness tend to be organized, responsible and hard-working. They are more likely to set goals for themselves and work diligently to achieve them [130]. This description fits well with the Performing and Expanding dimensions of the DEEP model, which involve achieving goals, whether low- or high-level, through mastered actions or strategies. The Performing dimension involves the use of familiar, mastered actions or strategies to achieve low-level goals, while the Expanding dimension involves the use of familiar, mastered actions or strategies to achieve high-level goals. Both dimensions imply a degree of mastery and consistency, which are characteristics associated with Conscientiousness.

To test this prediction, we ran two regression models, with participants' Performing and Expanding scores as dependent variables, and participants' Conscientiousness score as the independent variable. In both models, we predicted a significant and positive effect of Conscientiousness.

6.2.3. Prediction 3

The Expanding and Discovering dimensions, which involve high-level goals, should be positively associated with the Behavioral Identification Form, while the Performing and Experimenting dimensions, which involve low-level goals, should be negatively associated with it.

The Behavioral Identification Form [156] measures the personal level of agency, i.e., the level of abstraction at which individuals identify actions: at a high level of abstraction (i.e., in terms of broader goals or objectives) or at a lower level of abstraction (i.e., in terms of specific behaviors). As Vallacher and Wegner put it, "*it is possible to speak of individual differences in level of personal agency. At one extreme is the low-level agent, someone who operates on the world primarily at the level of detail. This person tends to approach an action with its mechanistic components in mind. At the other extreme is the high-level agent, someone who routinely views his or her action in terms of causal effects, social meanings, and self-descriptive implications. This person attempts to control action with respect to these consequence-defined identities*".

To test our prediction, we ran 4 linear models in turn, with each dimension as the dependent variable, and the level of personal agency measured by the BIF as the independent variable. We expected a positive relationship between Expanding/Discovering scores and BIF scores, and a negative relationship between Performing/Experimenting scores and BIF scores.

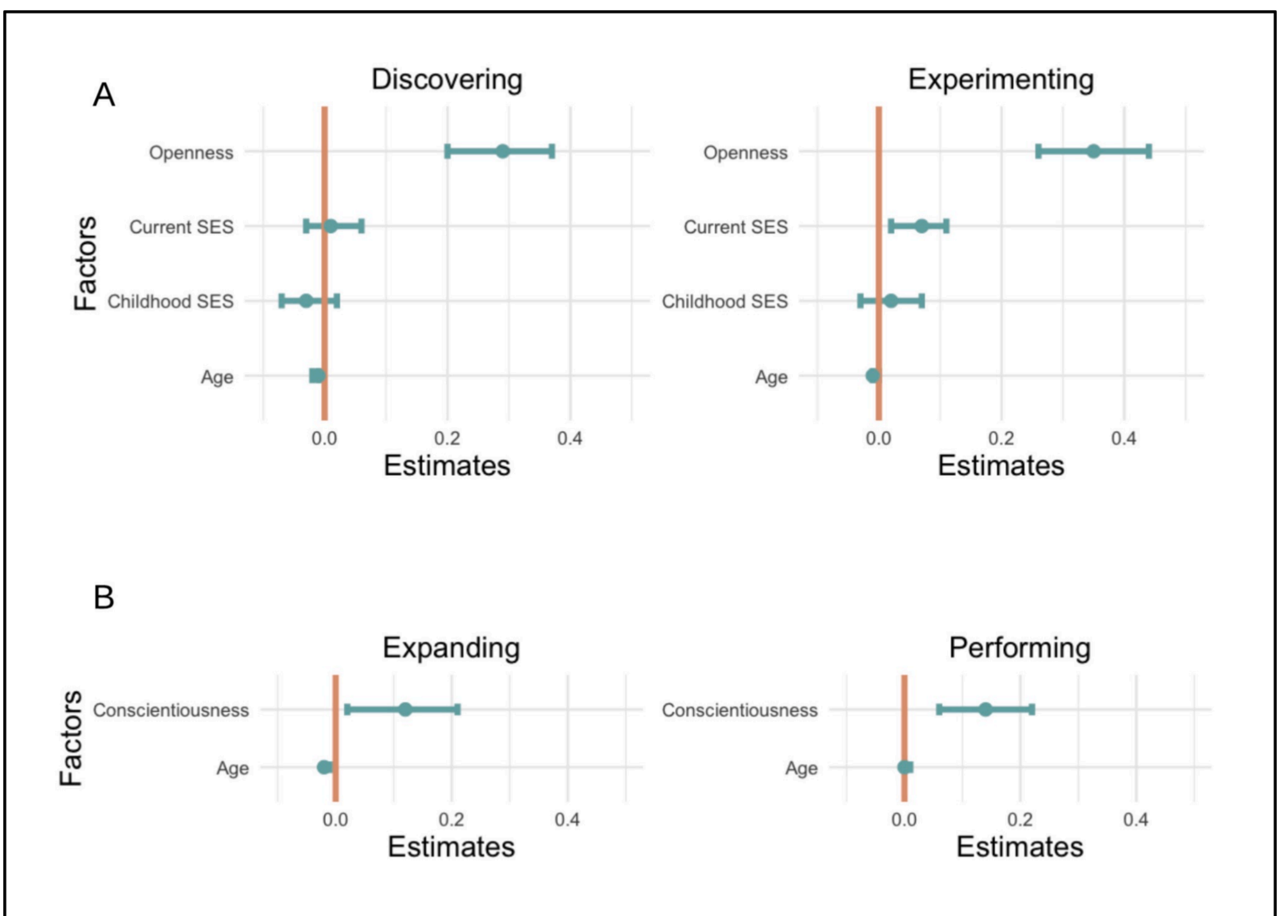

Fig. 8. A. Forest plot of beta coefficients estimated by two models, with the Discovering and Experimenting dimensions as the outcome variable of both models, and Openness scores, age, and childhood and current socio-economic status as explanatory variables. **B.** Forest plot of beta coefficients estimated by two models, with the Expanding and Performing dimensions as the outcome variable of both models, and Conscientiousness scores and age as explanatory variables.

6.3. Results

6.3.1. Prediction 1

In line with our initial hypothesis, the results of the regression models partially confirm the association between the Experimenting and Discovering dimensions and the variables Openness, Age, and Socio-economic status (see Fig. 8).

For the model predicting participant's Discovering scores, the results revealed significant effects of Openness ($\beta = 0.29$, $p < 0.001$) and age ($\beta = -0.014$, $p < 0.001$; see Supplementary materials for a correlation table with all 4 DEEP dimensions and all 5 traits of the Big 5). This result suggests that individuals with higher Openness scores and younger participants were more likely to score higher on the Discovering dimension. However, contrary to our predictions, both childhood socio-economic status ($p = 0.286$) and current socio-economic status ($p = 0.584$) were not significantly associated with the Discovering scores. Overall, the model accounted for 6.4 % of the variance in Discovering scores.

Similarly, for the model predicting participant's Experimenting scores, significant effects were found for the variables Openness ($\beta = 0.34$, $p < 0.001$) and Age ($\beta = -0.009$, $p = 0.005$). Again, individuals with higher Openness scores and younger participants were more likely to score higher on the Experimenting dimension. Interestingly, in this model, current socio-economic status was significantly associated with Experimenting scores ($\beta = 0.066$, $p = 0.006$), while childhood socio-economic status was not ($\beta = 0.018$, $p = 0.492$). The model accounted for 7.1 % of the variance in Experimenting scores.

6.3.2. Prediction 2

In line with our initial hypothesis, the results of the regression models provide partial support for the association between the Expanding and Performing dimensions and the variable of Conscientiousness (see Fig. 9).

For the model predicting participant's Expanding scores, the results revealed a non-significant effect of Conscientiousness ($p = 0.12$). This suggests that Conscientiousness scores do not impact the preference for the Expanding dimension.

For the model predicting participant's Performing scores, a significant effect was found for Conscientiousness ($\beta = 0.15$, $p < 0.001$). This result indicates that individuals with higher Conscientiousness scores were more likely to score higher on the Performing dimension. The model accounted for 1.3 % of the variance in Performing scores.

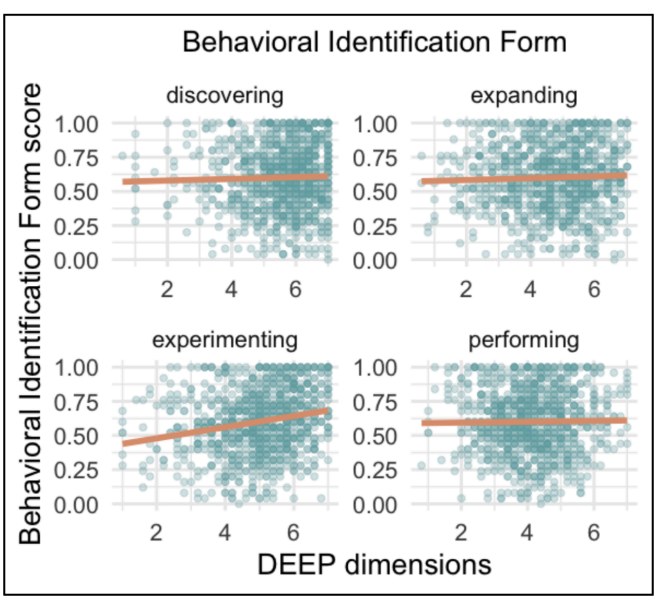

Fig. 9. Correlational plot between each DEEP dimension and the Behavioral Identification Form score.

In summary, our findings provide support for the hypothesis that Conscientiousness is associated with the Performing dimension, but not with the Expanding dimension. Further research is needed to clarify these relationships and to explore other potential influencing factors.

6.3.3. Prediction 3

Here, we examined the relationship between the BIF (Behavior Identification Form) and the four dimensions of player experience: Experimenting, Expanding, Discovering, and Performing. The BIF is a measure of an individual's tendency to interpret actions in terms of their higher-level goals or lower-level means. We predicted that BIF scores would correlate positively with high-level dimensions (Expanding and Discovering) and negatively, or not at all, with low-level dimensions (Experimenting and Performing). We performed a series of linear regression analyses with the BIF as the predictor and each of the four dimensions as outcome variables (see Fig. 9). The results did not support our prediction and proved somewhat counterintuitive.

The BIF showed a positive, but non-significant, relationship with the Expanding ($p = 0.23$) and Discovering ($p = 0.35$) dimensions, meaning that individuals with a higher tendency to interpret actions in terms of their higher-level goals (higher BIF scores) do not differ significantly in their preference for Expanding and Discovering in games, compared to those with a lower tendency (i.e., lower BIF scores). This result does not support our hypothesis that a higher BIF score would be associated with a stronger preference for these dimensions. Similarly, the BIF showed a non-significant positive relationship with the Performing dimension ($\beta = 0.07$; $p = 0.65$), suggesting that preference for Performing in games is not associated with a tendency to identify one's actions in terms of their low-level means.

The BIF showed a significant *positive* relationship with the Experimenting dimension ($\beta = 1.04$, $p < 0.001$), suggesting that individuals with a higher tendency to interpret actions in terms of higher-level goals showed a stronger preference for the Experimenting dimension. This was unexpected, as Experimenting is typically associated with a focus on the means, rather than higher-level goals.

In summary, the BIF did not significantly predict preferences for Expanding, Discovering, and Performing in games, thus failing to confirm our hypothesis. The significant positive relationship between the BIF and the Experimenting dimension was unexpected and somewhat counterintuitive. These results suggest that the relationship between action interpretation (as measured by BIF) and game preferences is complex and may not be easily captured by the action identification levels framework. We discuss these results in more detail below.

6.3.4. Exploratory analyses

Our exploratory analyses revealed intriguing relationships between the dimensions of the DEEP model and the different facets of curiosity measured by the Five-Dimensional Curiosity Scale (5DC – see Supplementary Material for the whole correlation table).

Firstly, the Experimenting and Discovering dimensions show a positive correlation with Joyous Exploration ($\beta = 0.33$ and $\beta = 0.20$ respectively; *both* $p < 0.001$). This relationship is consistent with the 5DC definition of Joyous Exploration, which refers to the desire to seek out new knowledge and information, and the consequent pleasure of learning and growing. Players who enjoy experimenting in the game are therefore likely to agree with 5DC items such as '*I enjoy exploring new ideas*' or '*I find it fascinating to learn new information*'.

Interestingly, the Performing dimension, which characterizes the preference for executing known actions or strategies, showed no significant correlation with joyous exploration. This suggests that people less intrinsically motivated to acquire new knowledge are more motivated to play games that allow them to perform rather than experiment or explore. On the other hand, the Performing dimension was negatively associated with the Stress Tolerance dimension ($\beta = -0.15$, $p < 0.001$), which refers to the willingness to embrace the anxiety associated with novelty. One possible interpretation of this negative association is that players who enjoy performing feel comfortable with what is familiar to them, as familiarity reduces the stressful experience associated with novelty. These findings underline the multifaceted nature of curiosity and the important role it plays in shaping player experience.

6.4. Intermediate discussion

Study 4 explored the psychological and socio-demographic factors influencing the dimensions of the DEEP model. The results highlight the complex interplay between individual differences, socio-economic factors and Video game preferences.

Openness and age emerged as significant predictors of the Experimenting and Discovering dimensions, with higher Openness and younger age associated with a tendency to score high on these dimensions. This association, which is in line with recent psychological and developmental accounts of curiosity, suggests that individuals who are more open to new experiences and younger players are more likely to enjoy exploring and experimenting within games. Interestingly, current socio-economic status was also associated with the Experimenting dimension, indicating that socio-economic factors may influence players' willingness to experiment within games. The relationship between Conscientiousness and the Performing dimension was also confirmed, with the most diligent and organized individuals preferring games that allow them to execute known actions or strategies. However, Conscientiousness did not significantly predict the Expanding dimension, indicating that this personality trait may not influence players' enjoyment of games involving information management.

The study also examined the relationship between the Behavior Identification Form (BIF) and the DEEP dimensions. The BIF measures an individual's tendency to interpret actions in terms of higher-level goals or lower-level means. Contrary to expectations, the BIF did not significantly predict preferences for the Expanding, Discovering, and Performing dimensions. We believe there are three possible reasons for this lack of correlation.

First, the significant correlation between the BIF and the Experimenting dimension can be understood in the context of the individual's motivation for progression and growth. According to [156], individuals who score high on the BIF tend to identify their actions at a higher level, associating them with their overarching goals rather than the specific steps they involve. This propensity is particularly pronounced for actions perceived as familiar, not overly complex and requiring little time to learn or implement. BIF scores may therefore measure the satisfaction derived not from achieving a high-level of action identification, but from the process of *elevating* their actions to a higher level, by *making* such actions more familiar and less complex. The Experimenting dimension may therefore cater to this inherent drive for progression and growth in individuals with a high BIF score, which may explain the correlation observed between the BIF and the Experimenting dimension, and the absence of such a correlation with the other gameplay dimensions. This interpretation should drive further research to explore such relationships in greater detail.

The other possibility is that the BIF does not test preferences for certain types of action, but a preferred level of action identification. However, there is no guarantee that the level at which people *identify* their action (as measured by the BIF) is the same as the type of action that people *prefer* to achieve (which is what the DEEP model assesses). The lack of correlation between BIF scores and the DEEP dimensions could be explained by this mismatch between the two measures.

The third possibility relates to a more general, and perhaps deeper, mismatch between the theory of action identification (BIF) and the framework of goal hierarchies from which the DEEP model is derived. Indeed, in goal hierarchies, goals at each level are interconnected, which explains why focusing on abstract or high-level goals can activate connected subordinate goals or means (top-down activation; [88]) whereas engaging in a low-level behavior can bring the connected superordinate goal to mind (bottom-up activation, Shah and Kruglanski, 2003). In action-identification theory, however, an action is identified either concretely or abstractly, and there is no interconnection or mutual activation of concrete or abstract identifications. This raises a fundamental difference between the assumptions underlying the BIF model and the DEEP model. In the BIF model, individuals are assumed to identify their action at either the concrete or the abstract level (but not both), whereas the DEEP model assumes that individuals can prefer both concrete and abstract levels of action, simply because goals are hierarchically organized, meaning that the desire to achieve abstract goals also requires an appetite for the more concrete goals that underpin these abstract goals. In other words, in goal hierarchies, concrete and abstract goal levels are not mutually exclusive, but complement each other (e. g. [20]; see Höchli for a review).

7. General discussion

Our research began with the development of the DEEP model – for Discovering, Experimenting, Expanding, and Performing – which we proposed as a theoretically informed framework for understanding the diverse motivations that drive individuals to play Video games, as well as empirically capturing the variety of preferences that guide their game choices and gameplays. The DEEP model has its origins in the hierarchical nature of goal-directed actions, which suggests that individuals' preferences for exercising one form of agency over another may explain inter-individual differences in game preferences.

Our first study involved a factor analysis of a wide variety of game-related actions that participants were asked to rate on an interest scale. Factor analyses revealed that game preferences varied along four latent dimensions that fit the DEEP model remarkably well. This finding provided empirical support for our theoretical framework and demonstrated its potential to capture the diversity of gamers' motivations.

Next, we used a Large Language Model to automatically annotate a wide range of video games based on each dimension of the DEEP model. This methodology has proven to be a fruitful approach. In particular, this method enabled us to test the hierarchical structure of goal-oriented actions in video games, providing further evidence for the validity of our model. As predicted, we observed that lower-level actions in video games were nested within higher-level actions, and that games satisfying lower-level goals – and only lower-level goals – were consequently more frequent than purely high-level games.

In our third study, we sought to quantify the ability of the DEEP questionnaire to predict people's preferred video games. Our results showed that the dimensions of the DEEP questionnaire could indeed predict players' preferences, but also their involvement in these games (e.g., time spent playing), confirming the status of the DEEP model as a robust and valuable tool for studying engagement in video games.

Finally, we delved into the psychological and socio-demographic underpinnings of the DEEP dimensions. Using various psychometric tests, we explored the relationship between DEEP dimensions and factors such as personality traits. Our results suggest that the DEEP dimensions are not only related to players' game preferences, but also to broader psychological and sociodemographic factors.

It should be noted that this work leaves room for many improvements and wider application possibilities. Study 1, for example, would benefit from a more in-depth factor analysis including a wider range of items, such as those encompassing high-level strategic actions. In addition, integrating questions on the social dimension of gaming could provide insight into the interaction between our dimensions and the social aspects of Video games. The exclusive recruitment of US participants limits the generalizability of our findings, pointing to the need for a more diverse and international group of participants to test the universality of these trends. For Study 2, replicating our findings with different datasets would strengthen the validity and applicability of our results. In studies 3 and 4, finally, it would be imperative to further investigate the relationship between personality psychology and gaming preferences. This involves exploring more nuanced links between real-world behavioral and psychological traits and their in-game counterparts. In what follows, we discuss the broader findings and future directions of this research.

7.1. The DEEP model and motivational needs

The complementarity of the DEEP model, which aims to characterize goal preference, and self-determination theory, which aims to characterize individuals' motivational dispositions, is self-evident: there is a clear relationship between individuals' motivational tendencies and the nature of the goals they seek to achieve [11]. In this respect, the DEEP model can be seen as a refinement of the Self-Determination Theory applied to Video games [127] (see [154], for a review). While Self-Determination Theory posits that player engagement is motivated by the satisfaction of general psychological needs – competence, autonomy, and relatedness –, the DEEP model offers a more nuanced understanding of these motivations, disentangling the different forms of motivational needs satisfied *when playing specific games*. Here, we proposed to further refine our understanding of these motivations by distinguishing between exploitative and exploratory motivational goals, and between high-level and low-level motivational goals.

Specifically, we believe that most theories aimed at explaining gaming preferences – including Self-Determination Theory – focus on what Nguyen [114] calls 'game *purpose*' (i.e., the general reasons why we engage in video games in the first place), whereas in this research we focused on 'game *goals'* (i.e., the many objectives we aim for while playing). These notions are not, however, easy to disentangle from each other. We argue that the purpose in playing a game precisely *derives from* the nested goals the game enables you to achieve (self-determined goals) or that it sets for you (designated goals). For instance, you cannot understand the general reasons why players of First-Person Shooters enjoy playing video games without examining the specific types of goals that can be achieved in these games. In other words, we argue that a detailed understanding of motivation to play video games cannot be achieved by considering general motivational needs alone.

It should also be noted that Self-Determination Theory emphasizes the presence of social motivations though the notion of 'relatedness'. Many other theoretical models aimed at characterizing players' motivations and preferences in video games include the social dimension as a key element (e.g., [164,136]). This is not surprising given the intrinsically social nature of many human activities and the fact that video games often provide a platform for social interaction (e.g., massively multiplayer online role-playing games, or MMORPG). However, in the DEEP framework, we argue that the social dimension is orthogonal to the core interactive elements that define video games and contribute to their appeal.

First, not all video games are social. Many games are single-player experiences, designed to be enjoyed in solitude. These games can offer deeply engaging and rewarding experiences without any social interaction. In fact, before the advent of the Internet, video gaming was primarily an individual activity. Classic examples include the original *Super Mario Bros*., *The Legend of Zelda*, and *Tetris*, all of which offered rich, engaging experiences without the need for social interaction. This tradition of solo gameplay continues robustly in the modern era, especially within the realm of mobile gaming. Today, some of the world's most popular video games are played on smartphones and often enjoyed alone, as evidenced by titles such as *Candy Crush Saga*, with over 500 million downloads, *Angry Birds 2*, *Super Mario Run*, and *Sonic Dash*.

Secondly, while social interaction can catalyze the enjoyment of a game, it is not a unique feature of video games. All human cultural activities, from music to movies to dance, can be used flexibly to achieve social goals [46,40,138,41]. Take cooking as an example: cooking can be a solitary pleasure or a shared joy, yet the fundamental appeal of the activity remains the same, whether practiced alone or with others. Social interaction may add an extra layer of enjoyment to the activity, but it does not alter the intrinsic qualities that make cooking enjoyable. We believe the same is true of video games.

Thirdly, even in exclusively multiplayer games, understanding the mechanics of the game remains crucial. Multiplayer games often share similarities with single-player games (e. g., *Metal Gear Solid* and *Tom Clancy's Rainbow Six Siege*). The question is: why do many multiplayer games use mechanics similar to their single-player counterparts? Our aim in this article is to elucidate the common characteristics of video games, whether single or multiplayer. The same applies to movies, which can be enjoyed alone or with others: while the social context may modify the viewing experience, it does not remove the need to understand the inherent appeal of a movie, whether experienced individually or in a group. Therefore, the social dimension is neither necessary nor sufficient to explain the appeal of video games.

The social dimension can of course explain some of the *variability* in gaming preferences. For instance, certain Video games (e. g., MMORPG) should appeal more to certain groups of people based on variable psychological traits (e. g., Extraversion). However, we believe that these research questions should be approached within a different conceptual framework, one that is independent of the medium under consideration and takes as its starting point the underlying psychological traits themselves (e. g., people higher in Extraversion should enjoy more video games that include multiplayer features, but also dancing with other people, watching movies with friends, etc.).

7.2. The DEEP model and the 'ludology versus narratology' debate

The results of the DEEP model provide some answers to the long-standing debate between narratologists and ludologists in Video game studies [1,76,85,112]. At its core, this debate revolves around the question of whether the main appeal of video games lies in their narrative aspects (storytelling), as argued by narratologists, or in their procedural aspects (gameplay, as instantiated by game mechanics), as argued by ludologists. The debate between narratologists and ludologists can thus be seen as a tension between story-driven and mechanics-centered approaches to game design.

We suggest here that this dichotomy is not necessarily a zero-sum game. The narrative and ludic elements of a video game can, and often do, work in tandem. Along with others, we propose that the narrative elements of a game, such as its plots and characters, help define the high-level goals that give context and meaning to the player's actions [151] (see also: [26]). These elements provide a framework within which players can exercise their agency, either by exploiting the information displayed by the cinematics (i.e., Expanding; e. g., the cutscenes in *GTA 5*, which, when compiled, amount to nearly 4 h and 55 min of purely narrative content), or by seeking out or constructing new narrative information themselves (i.e., Discovering; e. g., the player-generated narratives of *Sims* characters, which have inspired countless YouTube episodes featuring the unique stories crafted through gameplay). In a way, this distinction echoes Jenkins' division between "embedded narrative" and "enacted narrative" [76]. Embedded narrative refers to the story elements predefined by the game designers, while enacted narrative refers to the perceived unique story that unfolds through the player's interactions with the game world.

Importantly, high-level goals predefined by the game designer do not necessarily dictate the specific sub-goals and actions the player must undertake, allowing a certain amount of flexibility at lower levels of action planning, selection, and execution. The ludic elements of a game, such as its mechanics – i.e., the rules governing the player's interactions with the game world – provide the player with immediate, tangible tasks to accomplish, which may involve either *exploiting* known actions and strategies designed to achieve low-level goals (i.e., Performing; e. g., the straightforward mechanics of games like *Candy Crush*, which enable players to quickly master and excel at the game), or *exploring* new actions and strategies to achieve such goals (i.e., Experimenting; e. g., in games like *Celeste*, where each level presents unique challenges, requiring constant adaptation and experimentation from the player).

As predicted by our theoretical model, we observed that goals in video games are hierarchically nested, from concrete to abstract. This hierarchy can be represented as a high-level (abstract) narrative framework which, in order to be realized, requires the execution of lower-level objectives and actions, without the reverse being true (i.e., the possibility of achieving lower-level goals does not require the realization of higher-level – e.g., narrative – goals). Here, we show that this nested structure is a fundamental aspect of how gamers interact with and experience video games. In this respect, the ludologists' argument that game mechanics define the main appeal of Video games has some merit: all video games are intrinsically interactive; they require, even minimally, the implementation of low-level commands or concrete actions, whereas not all games include narrative elements, by virtue of the nestedness principle itself (see Fig. 5).

Acknowledging the foundational nature of game mechanics does not mean downplaying the power of narrative in video games. Narrative elements can be used to amplify the gaming experience by providing high-level goals and context – what Tanenbaum and Tanenbaum [151] refer to as 'narrative meaning'. This is increasingly evident in the tendency to exploit the entire hierarchy of goals in game design. Take the game *Celeste*, for example. At its core, *Celeste* is a platformer game with very low-level mechanics, much like *Mario Bros*. However, Celeste also includes a narrative that provides context and meaning to these challenges. The story revolves around Madeline, a young *trans*-woman, her depression, and her journey to climb Celeste Mountain. These narrative elements effectively allow players to engage with the game on a higher, more abstract level, and to "nest" all their in-game actions and subgoals into a broader hierarchy of goals. Here, the possibility offered by narrative elements of experiencing the game (its actions, goals and subgoals) at a higher level of the hierarchy is what helps make the game "meaningful". As such, we share with others (e.g., [26]) the view that video games can generate meanings that traditional media cannot: they can do so because they reflect the hierarchical nature of goal-directed actions, where higher-level elements in the hierarchy can amplify the value – whether motivational or emotional – of lower-level elements [38].

The DEEP model is an important step in taking *inter-individual variability* into account in the ludology/narratology debate: it allows for precisely measuring the extent to which individuals value high-level (e.g., narrative) over low-level (e.g., ludic) elements in video games, or vice versa. In this respect, we share Jenkins' [76] belief that there is no single future for games: "The goal should be to foster diversification of genres, aesthetics, and audiences, to open gamers to the broadest possible range of experiences". The DEEP questionnaire and AI-annotation of DEEP dimensions are two promising tools for embracing this diversity and empirically grounding the study of inter-individual variability in narration and gameplay preferences.

7.3. The DEEP model and exploration with unknown outcomes

The DEEP framework purposely separates exploitation goals from exploration goals. In both explorative dimensions (i.e., Discovering and Experimenting), we did not distinguish between exploratory behaviors aimed at experimenting with new *strategies* and exploratory behaviors aimed at discovering new *goals*. We suspect that these behaviors could be further dissociated to provide an even more nuanced understanding of exploration, in both real and digital environments.

This dissociation can be formalized as the difference between exploration *with* known outcomes and exploration *without* known outcomes, which seems to map the distinction between joyous and uncertainty-based forms of curiosity [73]. Exploration with known outcomes refers to the exploration of *new* actions associated with *known* low-level goals (e.g., trying out new tools to build something specific and familiar), or to *new* sub-goals associated with *known* high-level goals (e.g., taking the bus instead of one's car to work; see, e.g., [140]). Exploration with unknown outcomes, on the other hand, refers to the exploration of *new* low-level goals (e.g., using known tools to build something non-specific and novel) or for *new* high-level goals (e.g., taking your car to wander around). This new dimension of exploration without known outcomes could explain, in real environments, seemingly goal-free behaviors such as wandering or 'chilling out', which do not seem to be aimed at achieving specific goals. We argue that the underlying purpose of these behaviors is to discover new low- or high-level goals, whether this discovery is fortuitous or intentional.

This distinction between subsets of exploratory behavior takes on particular meaning in the context of Video games. Some games are geared toward discovering and experimenting, favoring exploration with *known* outcomes, while others encourage **wandering** and **tinkering**, favoring exploration with *unknown* outcomes. For instance, the game *Zelda* promotes exploration with known outcomes at a high level, as players are encouraged to discover and experiment with strategies to achieve specific goals. *No Man's Sky* or *Outer Wilds*, on the other hand, favor exploration without known, high-level outcomes: players are encouraged to wander and discover new goals, if not to set goals for themselves. Similarly, at a lower level, *Injustice* favors experimentation with known outcomes, as players tend to learn and gradually refine specific actions to achieve sub-goals (e.g., with a dedicated interface that displays the controller buttons alongside specific combo moves for each character), while *Super Smash Bros* favors experimentation with unknown outcomes, as players are encouraged to try out new actions without a clear understanding of their potential outcomes.

To capture these nuances, we suggest declining the exploration dimension into two distinct sub-dimensions of the DEEP model: one for exploration with known outcomes (i.e., a familiar action is diverted from its usual function to connect with a known goal) and one for exploration without known outcomes (i.e., a familiar action is performed to discover an as yet indeterminate goal; see below, Fig. 10). This extension would make it possible to model more finely the diversity of players' exploratory behavior in digital environments.

7.4. The DEEP model and game design

The DEEP model postulates that human agents engage in particular activities according to the type of agency they most enjoy exercising. This observation is supported by our factorial analyses, which show that game preferences cluster along dimensions (Performing, Discovering, Experimenting, Expanding) that reflect different ways of engaging with game content and mechanics. We believe that these dimensions offer valuable insights for designing more attractive and satisfying personalized gaming experiences.

In game design, the DEEP model can be used in two different ways. The first can be described as a "niche" approach and involves optimizing a game for a specific form of agentic experience. For example, a game like *Tetris* is heavily geared towards the Performing dimension, where players use familiar, mastered actions to achieve concrete goals. The appeal of the game lies in its simplicity and the satisfaction that comes from mastering its mechanisms. This approach can be particularly effective for games targeting a specific audience.

The second approach could be described as "generalist", and involves designing games that exploit the full hierarchy of objectives, allowing players to choose the agentic experience they prefer. *GTA 5* is a prime example of this approach. In this game, players can engage in a wide range of activities, from discovering new areas and experimenting with different strategies, to expanding their understanding of the game world and performing mastered actions. This flexibility allows players to tailor their gaming experience to their preferences, in a way that naturally enhances their engagement and satisfaction.

Other sandbox games, such as *Minecraft* and *No Man's Sky*, take the generalist approach to another level by offering players the opportunity to engage in all forms of agency, including Wandering and Tinkering. In these games, players are free to explore the game world without any

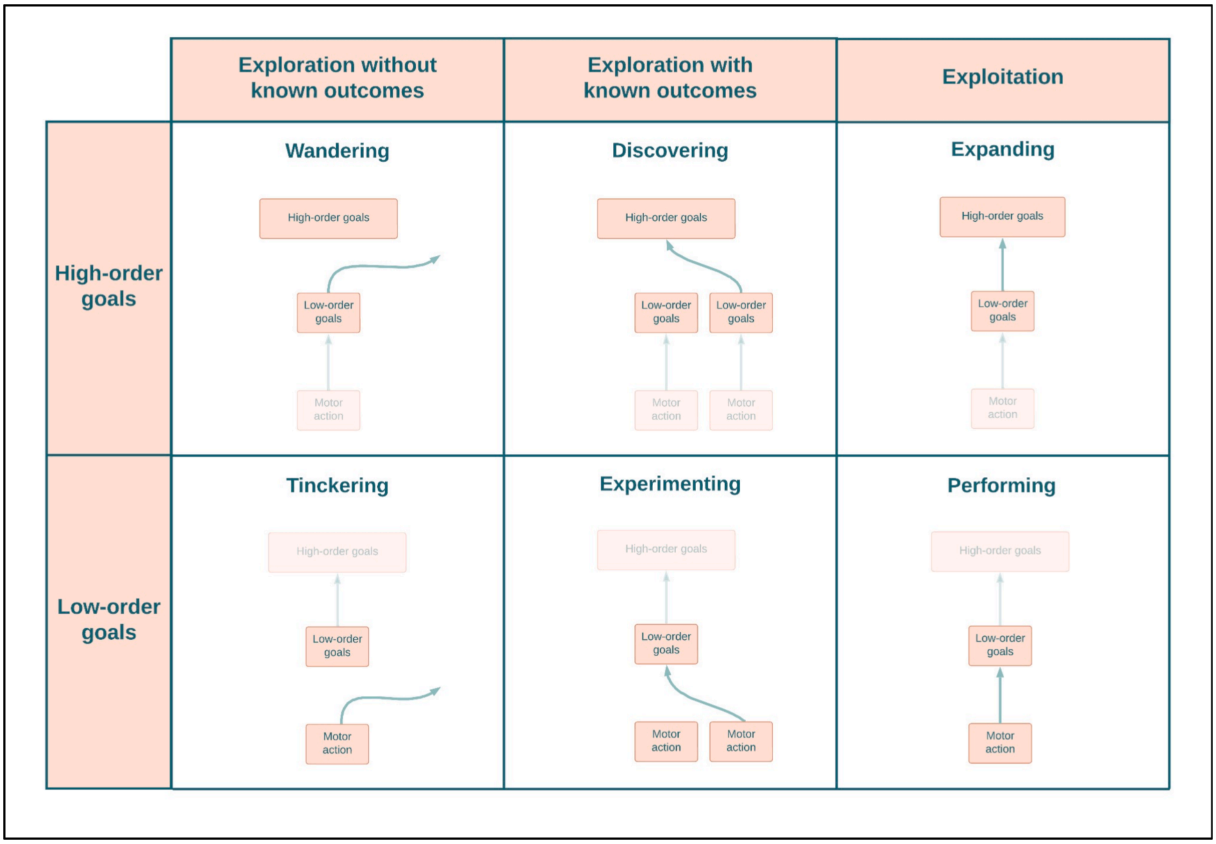

Fig. 10. A proposed extension of the DEEP model, with the addition of two new sub-dimensions. We distinguish a total of six dimensions: *Wandering* (i.e., using familiar, mastered actions or strategies to find new, high-level goals), *Tinkering* (i.e., using familiar, mastered actions or strategies to find new, low-level goals), *Discovering* (i.e., using actions or strategies in innovative ways to achieve known high-level goals), *Experimenting* (i.e., using actions or strategies in innovative ways to achieve known low-level goals), *Expanding* (i.e., using familiar, mastered actions or strategies to achieve high-level goals), and *Performing* (i.e., using familiar, mastered actions or strategies to achieve low-level goals).

predefined objectives, allowing them to discover new goals and experiment with different strategies at their own pace. Open game environments that allow wandering (or even "chilling out") can certainly have a strong appeal for some types of players, but it now remains to be tested whether these additional dimensions can increase the predictive power of our model, and whether they do correlate with identifiable underlying psychological dimensions.

8. Conclusions: The DEEP model and the hierarchical nature of goal-directed behaviors

This study started from the observation that there are many ways of interacting with the world, and that we can experience different ways of being an agent. We argued that the appeal of video games lay in their ability to emulate this diversity of experience by exploiting the fundamentally hierarchical structure of goal-directed cognition. It is worth noting that video games embody an *idealized* version of the agentic environment, where factors that usually detract from the quality of the agentive experience (e.g., the physical cost of action, the difficulty of "replaying" one's actions, the ambiguity of action feedback, etc.), are minimized. This idealization, which helps to amplify the agentive experience, also explains why video games are fertile ground for illusions of control (see the analysis of *Metal Gear Solid 4*'s final sequence in [151]).

However, this emphasis on agentive experience should not be taken as a call to *maximize* action capabilities in video games. Gamers do not necessarily want to experience agency at all costs; rather, they want to experience the type of agency they most prefer – a desire satisfied by video games such as *GTA*, which feature high levels of "*meta*-agency" (i.e., gamers can choose at will the type of agency they wish to exercise). We believe that this distinction between action capabilities and action preference is not trivial: it explains why certain games are preferred to others with similar action potential, but also why some people prefer games that seem *less* agentic, i.e., games where the possibilities for concrete action are lower. In fact, we suspect that the debate between narratologists and ludologists reflects, beyond its real theoretical stakes, differences in preferences for exercising one type of agency over another – i.e., either focused on narrative content (e.g., Expanding) or on game mechanics (e.g., Experimenting). In this sense, our proposal echoes [152] that it is not enough to provide players with *objective* control over the game for the game experience to be satisfactory. The player must also *desire* the proposed actions and the consequences of these actions. This desirability effect echoes, in cognitive science, the valence effect on agentive experience, where perceived agency is greater for positively, compared to negatively, valued action outcomes (e.g., [7,166] and positive events are more likely to be self-attributed by the participant, despite similar objective control [39,61].

Because it is based on two critical dimensions of goal-directed action (abstraction and exploration), the DEEP model sheds new light on research questions whose treatment sometimes lacks ecological validity. For example, most research into the experience of action involves invariably stable environments, where action-consequence mappings do not change, and where the subject's choice boils down to exploiting a single (low-level) action associated with a known or easily predictable effect (see [59], for a review). The results of our analyses indicate, however, that agentive experience may *vary* according to whether the action is oriented towards exploration rather than exploitation, or when the action is familiar, habitual or mastered (as opposed to new, with as yet undetermined goals or unknown outcomes). The dimensions of the DEEP model also suggest that agentive experience may vary depending on whether one is pursuing self-set goals or not, in line with recent work showing that perceived agency differs when action is self-determined vs. externally imposed [8,21,25]. The DEEP model thus offers an innovative framework for empirical research on agency, due to its ability to exploit the hierarchical structure of goal-directed behavior and capture the richness of the experience of human action in all its diversity.

9. Contribution

E.D. and V.C. conceived the main idea, designed the outline, and worked on the final paper. E.D. designed the experiment and analyzed the data. E.D. and V.C. wrote a first draft. All authors contributed to the article and approved the submitted version.

10. Statement

During the preparation of this work the authors used ChatGPT and DeepL in order to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

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CRediT authorship contribution statement

Edgar Dubourg: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization. **Valérian Chambon:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

Appendix A:. The DEEP questionnaire

Rate the statements below for how accurately they reflect how you generally feel about Video games. Take your time. Do not rate what you think you should feel, or what you wish you felt, or what you no longer feel. Be as honest as possible. If you hesitate, you can think of your favorite Video games to answer the question. You have 'Don't know/Don't apply' choice, if you think the question doesn't apply to your gaming experiences.

Each item is rated on an **interest scale**:

1. Not at all interested
2. Not very interested
3. Slightly interested
4. Neutral
5. Moderately interested
6. Very interested
7. Extremely interested
8. Don't know/Don't apply

Discovering:

1. Fulfilling sidequests that lead to new information
2. Looking for and completing all the sidequests
3. Discovering new places
4. Exploring or discovering new items
5. Accumulating collectible items

Expanding:

6. Watching cinematics that explain the backstory
7. Skipping the cinematics (R)
8. Listening to non-player characters
9. Finding out as many details of the story as possible
10. Relying on my understanding of the story

Experimenting:

11. Trying out new ways of using my weapons or tools
12. Inventing new strategies all the time
13. Discovering new ways to play
14. Experimenting things outside the role of my character
15. Executing new move or combo all the time

Performing:

16. Using the best move or combo over and over again
17. Following a predefined order of quests
18. Maintaining my strategy no matter what until it works
19. Using the same tool or weapon over and over again
20. Doing simple and repetitive tasks

Scoring instruction:
Items should be randomized.

Replace *NA* by 0 (see **Study 1**). Compute the average for each dimension and analyze each dimension separately (after having reversed the score of item 7).

Appendix B:. ChatGPT prompt for annotating Video games

Here is an equivalent prompt for all 4 dimensions to copy and paste into ChatGPT:

Welcome to the DEEP model for rating Video games! DEEP stands for Discovering, Experimenting, Expanding, and Performing, representing the four dimensions used to assess gameplay experiences. These dimensions provide a comprehensive framework for understanding the different aspects of Video games. Let's take a closer look at each of these dimensions:

1. Discovering (High-level Exploration): Discovering is about using novel and innovative actions or strategies to achieve abstract goals. Discovering involves actively exploring the game world, uncovering hidden secrets and engaging in non-linear gameplay elements. This includes the ability to undertake side quests or optional objectives that offer new insights, items or areas to explore.
2. Experimenting (Low-level Exploration): Experimenting is about using novel and innovative actions or strategies to achieve concrete

goals. Experimenting focuses on the player's ability to innovate and try out different strategies, approaches or play styles within the game's mechanics. This includes experimenting with different weapons, abilities, or tools to meet challenges or discover unique solutions.
3. Expanding (High-level Exploitation): Expanding is about using familiar, mastered actions or strategies to achieve abstract goals. Expanding emphasizes player engagement with the game's lore, storylines and characters. This involves delving deeper into the narrative, interacting with non-player characters, and seeking out additional details or lore-rich content.
4. Performing (Low-level Exploitation): Performing is about using familiar, mastered actions or strategies to achieve concrete goals. Performing focuses on the player's mastery of game mechanics and the execution of well-practiced strategies to achieve specific goals or tasks. This involves effective use of abilities, precise timing or skill-based gameplay elements.

Now, you will rate a Video game on a scale of 0 to 100 on all dimensions. These scores will reflect how well the game aligns with the characteristics and potential of these four dimensions. I will now provide the names of the Video games I would like you to rate, and you will assign scores accordingly. Tell me you are ready and wait for the first Video game.

Then, ChatGPT (approximately) returns:

I'm ready to assist in the DEEP model for rating Video games. Please provide the name of the first Video game you would like me to rate.

Then, I write in turn the title of each Video game we took as examples.

For **Tetris** the output of the LLM is:
Discovering (High-level Exploration): 20/100.

- Tetris is a relatively straightforward game with a simple goal: fit the different shaped blocks together to form complete lines and prevent the screen from filling up. There's not much room for high-level exploration or uncovering hidden secrets. However, players can still discover the best positions for the falling tetrominoes.

Experimenting (Low-level Exploration): 70/100.

- Tetris allows for significant experimentation within its set rules. Players can try different tactics, such as focusing on creating single lines, double lines, or waiting to achieve a 'Tetris' (clearing four lines at once). The game mechanics allow for strategic rotations and placements of tetrominoes.

Expanding (High-level Exploitation): 10/100.

- Tetris doesn't offer any deep narrative or lore-rich content for players to delve into. The game is purely mechanics-driven, with no characters or storyline to interact with or expand upon.

Performing (Low-level Exploitation): 90/100.

- The core of Tetris is about the mastery of the game mechanics and the execution of strategies to achieve specific goals (i.e., clearing lines). With each game, players have the opportunity to improve their skill, perfect their strategies, and learn how to respond more effectively to the increasing speed of the game.

For **League of Legends** the output of the LLM is:
Discovering (High-level Exploration): 70/100.

- League of Legends (LoL) offers a wide array of champions, each with unique abilities and play styles. Players can explore different strategies and synergies among champions and their items. The game also regularly updates with new champions, items, and patches, offering opportunities for continuous exploration.

Experimenting (Low-level Exploration): 80/100.

- LoL allows players to experiment with different champions, roles, and item builds in various game modes. Players can continuously refine their strategies in response to their opponents' choices, the current game state, and ongoing changes in the meta.

Expanding (High-level Exploitation): 60/100.

- While LoL is primarily a competitive multiplayer game, it has expanded its universe through various forms of media, including cinematic trailers, lore updates, and even music videos featuring its champions. Players interested in the lore can dive into these resources to better understand the world of Runeterra and its characters.

Performing (Low-level Exploitation): 90/100.

- LoL is a game that requires significant skill and strategy. Players need to master the mechanics of their chosen champions, understand the nuances of the map, cooperate with their teammates, and outmaneuver the opposing team. The competitive nature of the game encourages continuous performance improvement.

For **Life is Strange** the output of the LLM is:
Discovering (High-level Exploration): 80/100.

- Life is Strange allows players to explore and interact with a richly detailed world. The game encourages exploration by rewarding players with additional backstory and context if they take the time to look around and interact with their environment. The game's episodic nature also provides an element of suspense and unpredictability.

Experimenting (Low-level Exploration): 60/100.

- The game's unique time-rewinding mechanic allows players to experiment with different choices and observe their consequences. While the options are somewhat constrained by the game's narrative structure, this mechanic still allows for a degree of experimentation within given scenarios.

Expanding (High-level Exploitation): 90/100.

- Life is Strange features a deep, character-driven narrative. Players can expand their understanding of the story by interacting with other characters and finding various hidden clues throughout the game. The narrative is multi-layered, and players can delve into different storylines, themes, and character backgrounds.

Performing (Low-level Exploitation): 50/100.

- Life is Strange is a narrative-driven adventure game, so it doesn't focus heavily on the mastery of complex mechanics or skill-based gameplay. However, the game does require players to make choices under pressure, search for relevant clues, and interact effectively with the game's environment.

For **No Man's Sky** the output of the LLM is:
Discovering (High-level Exploration): 95/100.

- No Man's Sky is practically built around the concept of exploration. The game features a procedurally generated universe with virtually limitless planets to discover, each with its unique flora, fauna, and resources. The vastness of the game world offers endless opportunities for high-level exploration.

Experimenting (Low-level Exploration): 90/100.

- The game encourages players to experiment with various elements like resource gathering, crafting, trading, combat, and survival strategies. Players can also experiment with different ship and multi-tool configurations to suit their preferred playstyle.

Expanding (High-level Exploitation): 70/100.

- While No Man's Sky initially lacked a strong narrative, updates have added lore-rich content, characters, and quests that give depth to the game's universe. Players can expand their understanding of the universe's history and the factions that inhabit it through these narrative elements. Performing (Low-level Exploitation): 85/100
- No Man's Sky requires players to master various game mechanics for survival, such as managing resources, upgrading equipment, and engaging in space and land combat. Performing well in the game often involves executing strategies effectively to navigate the game's vast universe and its challenges.

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.entcom.2025.100930.

Data availability

I have shared the link to my data/code in the manuscript

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