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Latent profiles of effort roles and their impact on task experience and behavior

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Abstract

The experience of effort is a decisive factor for engagement and behavior. However, exerting effort can yield vastly diverse experiences. We posit that these differences are due to distinct configurations of different roles of effort for self-regulation (instrument, reward, adding value to an outcome), and are influenced by task context (entertaining/learning). Furthermore, we investigate how these profiles of effort roles affect the decision to exert further effort. In our online study, 471 participants (51% female, 48% male, $M_{age} = 41.1 \pm 11.9$) were given an instructional framing (entertainment/learning game) and reported their anticipated strength of effort roles regarding the upcoming task. Participants then had the opportunity to play Tetris. Given that successfully playing Tetris requires constant attention and a certain amount of exertion, and it can be easily framed as either an entertainment or learning game, it serves as an appealing effort task for this study. Subsequently, participants indicated their task experience and their willingness to engage in further gameplay. A latent profile analysis identified four configurations of effort roles. These effort profiles significantly differed in the experience of positive and negative affect, boredom, perceived exertion in gaming, and willingness to engage in further gameplay. The impact of task framing was limited to negative affect and RPE. Our findings underscore the critical role of effort's roles in task experience and behavioral decisions.

Keywords Roles of effort for self-regulation · Task framing · Serious gaming · Latent profile analysis

Introduction

Exerting effort is a fundamental aspect of everyday life. Many researchers conceptualize effort to be inherently aversive and unpleasant (Chong et al., 2017; Kool & Botvinick, 2014), a view that has been further supported by a recent meta-analysis (David et al., 2024). However, as effort is linked to success, it is often exerted to achieve worthwhile goals, despite its aversive nature (e.g., Kurzban, 2016). Conversely, accumulating evidence suggests that effort can, under certain circumstances, be experienced as positive and inherently rewarding (Csikszentmihalyi, 1990; Milyavskaya et al., 2021). Indeed, some individuals appear to actively seek effortful activities for the sake of exerting effort itself (Zerna et al., 2023).

This variability in the subjective experience of effort may be crucial for understanding why people choose to engage in or avoid effortful activities (Maltagliati et al., 2024). A potential explanation for these differences lies in the different roles that are fulfilled by effort in self-regulation (Inzlicht et al., 2018; Zerna et al., 2023). Accordingly, this study examines the interplay of effort's different roles and their impact on affective states (e.g., positive and negative affect) within the context of a computer game. Additionally, we investigate how the situational context (entertainment or learning game) influences these relations and how the profiles differ in their willingness to exert effort in an allegedly subsequent task.

Effort's roles for self-regulation

Empirical and theoretical work asserts that the decision on whether and how much effort is applied is a reward-based

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choice (e.g., Atkinson, 1957; Shenhav et al., 2013; Skvortsova et al., 2014; Wolff & Martarelli, 2020). Individuals weigh the costs of effort against the rewards it may yield, aiming to maximize the overall value (Inzlicht et al., 2018; Shenhav et al., 2013). Interestingly, beyond its inherent costs (Chong et al., 2017), effort might also be rewarding in itself or enhance the perceived value of an outcome (Inzlicht et al., 2018).

First and most prototypically, effort serves as a means to achieve specific goals deemed valuable enough to justify the associated costs, thereby functioning as a costly instrument (effort-as-instrument) (Inzlicht et al., 2018; Stähler et al., 2025). This is reflected in many theories highlighting the instrumentality of effort (e.g., Brehm & Self, 1989; Duda, 1987; Sarrazin et al., 2002) and can be exemplified by a student who allocates just enough cognitive effort to achieve a desired grade. Second, individuals sometimes exert effort because they find it inherently enjoyable (Inzlicht et al., 2018), suggesting that effort holds inherent value in its own right (effort-as-reward) (Campbell et al., 2025). For example, a student might choose to spend hours working through a difficult math puzzle – not for a grade or recognition, but because the mental challenge itself is enjoyable. Third, the exertion of effort may increase the subjective value of an outcome, making success feel more rewarding (effort-as-adding-value) (e.g., Norton et al., 2012). To illustrate, a student who worked especially hard to earn a good grade might value that success more than an equally good grade that came with little effort. Here, effort not only incurs costs but also amplifies the perceived value of the outcome (Bogdanov et al., 2022; Wu & Zheng, 2023). These examples illustrate that effort can assume different roles in the self-regulation of behavior, corresponding to different conceptualizations of effort in goal pursuit (Inzlicht et al., 2018).

Given that effort can fulfill these different roles, it is plausible that their relevance varies across individuals and tasks (Wolff et al., 2024). For instance, a chess aficionado might primarily enjoy the cognitive effort of playing chess (effort-as-reward), while also perceiving it as an instrument for improving strategic thinking (effort-as-instrument) or anticipating the satisfaction of winning a challenging match where effort enhances the victory (effort-adding-value). For others, however, the efforts involved in playing chess may not align with any of these roles, and they may therefore rarely play chess. Accordingly, these roles are not mutually exclusive; they can occur simultaneously and vary in significance depending on the person and the activity. However, distinct configurations of these roles are likely linked to specific patterns of effort expenditure.

The Expected Value of Control (EVC) posits that individuals allocate cognitive control by weighing the expected benefits of exerting effort against its associated costs to maximize overall utility (Shenhav et al., 2013). Building on this, it can be anticipated that the more roles are fulfilled by effort, the higher its overall expected value (EV, see Fig. 1) and, consequently, the greater an individual's willingness to exert effort (Stähler et al., 2025). When effort is used solely as an instrument (Fig. 1A), individuals evaluate its inherent costs relative to the value of the outcome, adjusted by the probability of achieving it. If the outcome is both likely to be attained and sufficiently valuable, individuals are motivated to exert effort to achieve it. Conversely, when the costs outweigh the expected outcome, effort is likely to be avoided. However, when effort has an inherent value beyond its instrumental role (Fig. 1B), this inherent value is added to the value of the outcome, thereby increasing the overall EV. As a result, individuals are more likely to exert greater effort, even if the objective value of the outcome remains unchanged. Similarly, when effort adds value to an outcome (Fig. 1C), the perceived value of the outcome increases as a function of the effort exerted. Consequently, with increasing effort, not only do effort costs rise, but the perceived value of the outcome (adjusted by the probability of achieving it) also increases. Thus, the more roles effort fulfills (effort-as-instrument, effort-as-reward, or effort-adding-value), the higher the overall EV and the more likely individuals are to invest (greater) effort (Fig. 1D).

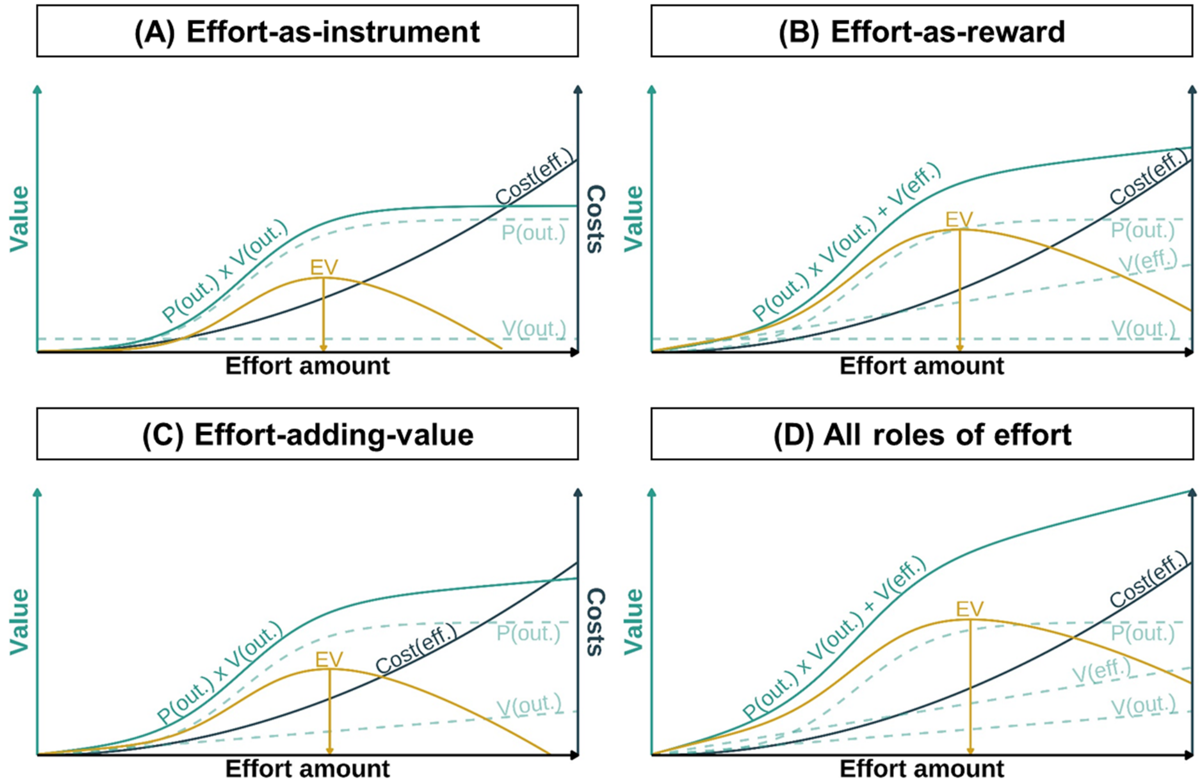
Fig. 1 The expected value (EV; yellow) and how it is composed per role of effort

While prior research has primarily addressed the roles of effort from a conceptual and theoretical perspective (e.g., see Inzlicht et al., 2018), empirical studies that systematically distinguish these roles remain scarce (for a review, see Stähler et al., 2025). To address this gap, the present study applies a person-centered approach to assess these roles and identify distinct latent profiles of effort roles. This approach allows for a nuanced understanding of how the effort roles co-occur within individuals.

Importantly, we go beyond identifying these profiles by examining how they relate to the subjective experience of effort. While the roles of effort may help explain why individuals differ in their willingness to exert effort, they may also shape the way effort is perceived and experienced on an affective level. To gain a more comprehensive understanding of these affective consequences of effort exertion, the following section reviews research on how effort is perceived and how it relates to affective states.

The experience of exerting effort

The experience of an activity is a crucial factor in determining whether people continue to engage in it and whether they will repeat it (e.g., Maltagliati et al., 2024). Positive



Note: Adapted from Inzlicht et al., 2018 and Stähler et al. (2025). Individuals allocate cognitive control by balancing the expected benefits of effort against its costs to maximize the expected value (EV). The parameters are represented as functions: The solid green line represents the combination of the dashed lines (sum and product), and the expected value (EV; yellow) is calculated by subtracting the costs (dark blue) from the benefits (solid green). The curves should be determined empirically. As the empirical curves are unknown, we employed exemplary functions. **(A)**: The expected outcome (solid green) is the product of the value [V(out.)] and the probability [P(out.)] of effort's outcome. Subtracting the effort costs (dark blue) from the expected outcome yields the expected value (yellow). **(B)**: Effort's inherent value [V(eff.)] is added to the expected outcome. Thus, also, the expected value increases, with a maximum at a greater effort level (yellow). **(C)**: As in (A), the expected outcome (solid green) combines the outcome's probability [P (out.)] and its value [V (out.)]. Unlike (A), the outcome's value rises with increasing effort, leading to a higher expected value. **(D):** The expected outcome (solid green) is effort's inherent value added to the product of the value [V(out.)] and the probability [P(out.)] of effort's outcome. As in (C), the outcome's value rises with increasing effort. This leads to a greater expected outcome (solid green), also for higher efforts, and thus, also to higher expected values (yellow).

affect, “reflects the extent to which a person feels enthusiastic, active, and alert” (Watson et al., 1988, p. 1063). High levels involve feelings of joy, focus, and engagement, whereas low positive affect is marked by sadness and low energy (Watson et al., 1988). Empirical evidence suggests that positive affect is linked to task engagement and repeated participation (Greitemeyer, 2009; Isen & Reeve, 2005). In contrast, negative affect encompasses the experience of unpleasant mood states such as anger, fear, guilt, or disgust, while low negative affect reflects calmness and emotional stability (Watson et al., 1988). Negative affect, as well as boredom, are related to disengagement (Garbarino & Edell, 1997; Wolff & Martarelli, 2020). These affective responses influence behavior and persistence, ultimately affecting success in achieving long-term goals (Duckworth et al., 2007). Importantly, engaging in effortful activities can yield vastly diverse experiences, such as variations in the accompanying affect (e.g., Csikszentmihalyi, 1990; Garbarino & Edell, 1997; Wolff, Stähler et al., 2024) and the perception of how effortful a task is (Milyavskaya et al., 2021).

In general, exerting effort seems to be a rather negative experience, as it is often perceived as aversive and unpleasant (David et al., 2024; Kool & Botvinick, 2014; Kurzban, 2016; Silvestrini & Gendolla, 2019). Effortful tasks can elicit stress, anxiety, negative affect (Garbarino & Edell, 1997; Inzlicht & Al-Khindi, 2012; Saunders et al., 2015), and fatigue (Inzlicht & Al-Khindi, 2012; Saunders et al., 2015). Consequently, people often try to avoid exerting effort to save resources (Brehm & Self, 1989; Cheval & Boisgontier, 2021). This tendency is reflected in their behavior; when given a choice, individuals select the less effortful option in the majority of cases (Dunn et al., 2016), and tasks requiring effort are selected less frequently (Garbarino & Edell, 1997).

In contrast, in some situations, and for some individuals, exerting effort is pleasant (Csikszentmihalyi & LeFevre, 1989) and enhances positive affect (Rogatko, 2009). This positive experience of effort is also reflected in behavior (Milyavskaya et al., 2021), as not everybody, and not in every situation, avoids effort (Inzlicht et al., 2018; Stähler et al., 2025; Zerna et al., 2023). Quite the contrary, some people even seem to seek effortful activities (e.g., Zerna et al., 2023). We posit that, among other factors, the distinct roles of effort in self-regulation (effort-as-instrument, effort-as-reward, effort-adding-value) are one reason for the diverse effort experiences and expenditures.

Each role of effort potentially enhances the expected value (EV) of effort exertion (Campbell et al., 2025), and this increase might influence the accompanying affective experience (Zerna et al., 2023). To illustrate, low value is one main characteristic of boring situations (Bieleke et al., 2021; Pekrun, 2006). Consequently, for individuals valuing effort (in any of its roles), a task is less likely to elicit boredom. Consistent with this, a recent study demonstrated that students who inherently valued cognitive or physical effort experienced less boredom and achieved better grades in the corresponding school subject (cognitive effort – math, physical effort – sports) (Wolff et al., 2024). Therefore, focusing on multiple roles of effort is likely to result in greater effort and less boredom (Thoman et al., 2011; van Tilburg & Igou, 2017; Wolff, Stähler, et al., 2024). Similarly, we would expect that the higher the EV, the more positive individuals will experience the exertion of effort (Zerna et al., 2023). And, thus, the more roles effort has simultaneously, the more positively the exertion of effort will be experienced. Further, as we expect a higher EV for effort-as-reward than for effort-as-instrument (see Fig. 1), we also expect a more positive effort experience for this role of effort.

In addition to the content-based qualitative distinction in the roles of effort, the quantitative dimension must also be considered. A straightforward measurement of perceived exerted effort can be achieved using the Rating of Perceived Exertion scale (RPE; Borg, 1998). It is important to note that perceived exertion can differ from objective effort, which refers to the actual energy exertion in performing a task (Steele, 2020). While these measures are often aligned, (Weilharter et al., 2024), they can also diverge even when task demands are objectively equal (Dunn et al., 2016). For example, during flow states, individuals subjectively perceive a task as relatively effortless, despite exerting considerable objective effort (Csikszentmihalyi, 1990). Likewise, interest in an activity has been shown to reduce perceived exertion and fatigue (Milyavskaya et al., 2021; Song et al., 2019). These findings suggest that the RPE is influenced by factors beyond its objective demands. When individuals find an activity interesting they might assign it greater value, which in turn makes the effort invested feel less exerting. Supporting this, individuals with a higher need for cognition tend to engage more willingly in cognitively demanding tasks and report them as less effortful (Zerna et al., 2023). Building on this, we propose that the simultaneous activation of multiple effort roles may create a comparable discrepancy between objective and perceived effort. As these roles increase the overall EV of a task, the same level of objective effort is likely to feel less demanding, reducing perceived exertion. However, this hypothesis has not yet been empirically tested.

Taken together, the same effortful task can result in different subjective experiences across individuals. We argue that such variations in experience and behavior can to some extent be attributed to distinct underlying roles of effort in self-regulation. While previous research has provided valuable insights into how effort exertion is experienced, there is a lack of empirical work that directly examines how different roles of effort influence this experience. Addressing this gap, the present study investigates the interplay of three effort roles and their relationships with affective state, boredom, perceived exertion, and decisions on behavior. In doing so, we aim to uncover how distinct effort profiles contribute to differences in the experience and regulation of cognitive effort.

Contextuality

Beyond individual differences, situational factors may shape how effort is evaluated and experienced. In particular, the context in which effort is exerted may influence the motivational meaning of effort. For instance, working towards a goal is associated with exertion and concentration, whereas playing is associated with freedom, diversion, and joy (Mitgutsch, 2009), although effort has to be exerted likewise in both learning and play. Thus, the same amount of effort is eventually evaluated more positively in leisure than in the learning context, resulting in a more positive affective reaction to exerting effort (Mitgutsch, 2009), and might influence the subjective perception of exertion (Steele, 2020). For example, a student might feel exhausted when reading a novel for school as mandatory reading but invigorated when reading the same novel at leisure.

While these theoretical distinctions are well acknowledged, empirical research has yet to systematically examine how effort roles interact with situational context to shape subjective task experience. To illustrate, when effort is primarily used as an instrument to achieve something, it aligns well with the learning context, where the primary focus is on achieving goals. In contrast, during leisure activities, the emphasis is more on fun and enjoyment, which could prevent efficient goal pursuit, and thus lead to negative affect and frustration. However, it remains unclear how the same roles of effort might lead to different experiences depending on whether the task is framed as a learning game or a leisure activity.

The present study addresses this gap by varying the context of effort exertion (i.e., entertainment vs. learning game) and examining its association with task experience. Furthermore, we investigate how context moderates the relationship between effort roles and task experience, thereby providing new insights into the dynamic interplay between the roles of effort and situational framing.

The present study

Consistent with recent work (Inzlicht et al., 2018), we expect that three roles of effort in self-regulation (effort-as-instrument, effort-as-reward, effort-adding-value) co-occur in people, resulting in different configurations of effort roles. Simply put, one person might mostly treat effort as an instrument but also find it rewarding to some degree, whereas another person might only treat it as an instrument. To investigate this, we employ latent profile analysis to assess if people differ with respect to their effort-role configurations. We expect that for most individuals, effort serves primarily as an instrument to reach goals. We also anticipate that for some individuals effort has a particularly high inherent value (effort-as-reward). In contrast, we consider it less plausible that effort is primarily valued because it enhances the outcome's value. Rather, we suspect that this role (effort-as-adding-value) may emerge secondarily when effort is already experienced as instrumental or rewarding. Lastly, we expect profiles in which all three roles are salient, as well as profiles in which effort hardly fulfills any role. However, given the lack of prior empirical research on the profiles of effort roles, these assumptions are based on conceptual plausibility, and the analyses remain exploratory.

Secondly, we evaluate the differences between the emerged profiles in predicting task experience, namely positive and negative affect, boredom, as well as perceived exertion after exerting effort. In general, we expect that profiles characterized by high scores across multiple roles of effort will exhibit low levels of negative affect and boredom, accompanied by high levels of positive affect and perceived exertion. In terms of the individual roles of effort, we hypothesize that profiles with only a particularly high instrumentality of effort are associated with the commonly reported aversive effort experience reflected in low positive and high negative affect and high boredom. Besides, we expect them to avoid exerting effort and, thus, report low values of perceived exertion. On the other hand, we assume that profiles with a high inherent value of effort (effort-as-reward) will be associated with effort experiences similar to flow. Specifically, we expect them to report greater positive affect and less negative affect and boredom than instrumental profiles or profiles with no distinct role of effort. Additionally, we assume that individuals belonging to effort-as-reward profiles would exert more effort than the instrumental profiles and, thus, report higher perceived exertion.

Thirdly, to investigate contextual influences, we employ a video game as a methodological tool to experimentally induce a task context (entertainment vs. learning). Games are particularly suitable for this purpose, given their inherent combination of fun and learning elements. Designating a game as entertaining or learning through sociocultural labels affects the motivation a person has (Csikszentmihalyi & LeFevre, 1989). The same game can be introduced (i.e., framed) in the study instructions as either an entertainment game emphasizing joy and entertainment or as a learning (i.e., serious) game emphasizing learning and performance. We hypothesize that the situational context, which implies different goals of effort application, will moderate the relationship between the latent profile of effort roles and reported task experience. Given that this context manipulation particularly alters the task's instrumental value, we expect the moderating effect to be especially pronounced for profiles with a high instrumentality of effort. Presumably, the learning context will result in a more positive experience for such profiles, as it reinforces the instrumentality of effort. Conversely, the entertainment context is expected to yield a more negative experience for effort-as-instrument profiles, as it mitigates the instrumentality of effort. On the other hand, the task framing should not significantly influence profiles with high effort-as-reward.

Furthermore, recent studies suggest that the willingness to exert effort depends on the roles of effort for self-regulation (e.g., Dunn et al., 2016; Thoman et al., 2011). Building on these findings, we investigate whether different latent effort profiles differ in the actual playtime in this study and how the profiles relate to individuals' willingness to exert effort in an allegedly subsequent task. We expect that the profiles of effort roles characterized by high scores on many roles or by a high effort-as-reward are associated with a greater willingness to exert effort than those where none of the roles is focused.

Methods

Participants

630 respondents were recruited from Amazon Mechanical Turk (recruitment criteria: CloudResearch-approved, U.S. residence, at least 90% approval rate, at least 100 HITs), of which five hundred completed the study. Further, twenty-nine participants had to be excluded due to the following reasons. One person indicated not participating seriously, $n = 13$ had technical issues, and $n = 15$ participated via tablet or smartphone and thus could not play the game properly. All remaining participants completed the study on a computer, as required. The final sample consisted of $N = 471$ participants (51.0% female, 48.4% male, 0.6% no answer) with a mean age of $M = 41.7$ (± 11.9).

The assignment to the task framing groups (i.e., entertainment or learning game) was random and computer-based via the survey tool LimeSurvey (LimeSurvey GmbH, n.d.). 211 participants were assigned to the learning (50.2% female, 49.3% male; $M_{age} = 41.0 \pm 11.2$) and 260 participants to the entertainment task framing (51.5% female, 47.7% male; $M_{age} = 42.3 \pm 12.5$). The study is in accordance with the Declaration of Helsinki and the ethics committee of the authors' institution did not demand a further IRB assessment (RefNo: IRB24KN006-05/w).

Although MTurk enables access to a heterogeneous participant pool (Buhrmester et al., 2011), the sample may still be biased toward individuals with higher digital literacy and education levels, and participation is limited to U.S. citizens (e.g., Huff & Tingley, 2015; Munger et al., 2023). While suitable for the study's aims and consistent with current psychological research practices (Buhrmester et al., 2011), this should be considered when interpreting the generalizability of the findings.

A statistical power analysis indicated that the attained sample size exceeds the threshold required for the planned statistical tests (Faul et al., 2007). For an ANOVA with a medium effect size ($f = 0.25$), a power of 95%, and an alpha level of 0.05, it is indicated that if we identify four latent profiles, a total sample size of 279 participants is needed. However, for conducting a latent profile analysis it is advised to have about 500 participants (Finch & Bronk, 2011).

Procedure

The study was conducted online via LimeSurvey (limesurvey.org) on participants' own devices. It took approximately twenty minutes and was compensated with 2.00 USD.

First, participants confirmed informed consent, verified to be human participants, and entered their Amazon MechanicalTurk worker ID. Then the weekly gaming duration was measured, followed by the introduction to the game Tetris, designating Tetris either as entertainment or as a learning game depending on the group assignment (find the task framings SI1 in the OSF: https://osf.io/g9mw4). To ensure that participants read and understood the information about Tetris, they had to summarize it in a free text field and answer questions about the information. Then the anticipated roles of effort for self-regulation in the upcoming match of Tetris were assessed. After receiving a short instruction on how to play this particular version of Tetris (see SI 2 in the OSF: https://osf.io/g9mw4) and having the opportunity to play Tetris for at least ten minutes, the participants filled in the state measures of perceived exertion, boredom, and positive and negative affect. At the end of the online study, participants were asked how much of the intended ten-minute play time they approximately played (a timer was given on the screen while they played) and which device they used (i.e., computer, tablet, smartphone). Additionally, they were asked how familiar they were with Tetris before participating in this study (i.e., "Never heard of this", "Not very familiar", "Somewhat familiar", "Very familiar"). As a manipulation check, we asked whether they see Tetris more as a serious or entertainment game ("Tetris for me is more of a …", "Serious game", "Entertainment game"). Furthermore, they were asked whether they wanted to play another round of Tetris after finishing the study ("Yes", "No"). Then participants indicated age (select from a dropdown menu) and gender (i.e., “female”, “male”, “no answer”) and whether they participated seriously in the study (i.e., “I did participate seriously in this study”, “I did NOT participate seriously in this study”). Lastly, participants were debriefed on the purposes of this study. More variables were collected as part of this study but only those relevant to this article are presented here (for the entire course of study, see OSF: https://osf.io/g9mw4).

Measures

Weekly gaming volume

We assessed the current gaming behavior by asking about the average weekly gaming frequency (“How often do you play video games per week?”) and gaming duration (“How long (in minutes) does a gaming session take you on average?”). The answers were given in numbers (frequency) and minutes (gaming duration) and were multiplied to calculate the weekly gaming volume.

Roles of effort for self-regulation

We developed three pairs of items, with each pair designed to capture one role of effort for self-regulation (see Table 1). Answers were given on a 7-point Likert-type scale, ranging from (1) “strongly disagree” to (7) “strongly agree” and were aggregated to a mean score per effort role with higher values reflecting greater agreement with the respective role of effort. The reliability in our sample was excellent for each effort role with Spearman-Brown-Coefficients of $r_{SBinstrument}$ = 0.83, $r_{SBreward}$ = 0.87, $r_{SBadding}$ = 0.91, which is suggested to be a suitable measure of internal consistency for two-item scales (Eisinga et al., 2013).

Table 1 The six items measure the anticipated roles of effort for self-regulation in an upcoming game. They are displayed per role of effort

Effort roles	Item
Effort-as-Instrument	1. I'm looking forward to exerting myself in the video game because it helps me achieve my goals.
	2. I'm looking forward to exerting myself in the video game because it pays off.
Effort-as-reward	3. I'm looking forward to exerting myself in the video game because I genuinely enjoy the effort.
	4. I'm looking forward to exerting myself in the video game because I like exertion.
Effort-adding-value	5. I'm looking forward to exerting myself in the video game because effort sweetens my accomplishments.
	6. I'm looking forward to exerting myself in the video game because it helps me cherish my accomplishments.

State positive and negative affect

The affective state was measured with the *Positive and Negative Affect Schedule* (PANAS; Watson et al., 1988). It consists of a positive affect scale (10 items, e.g., “active”, “interested”, “enthusiastic”) and a negative affect scale (10 items, e.g., “distressed”, “guilty”, “scared”). Respondents rated the extent to which they experience the affects using a 5-point Likert-type scale, ranging from (1) “not at all” to (5) “extremely”. Positive and negative affect items were aggregated to a mean score, respectively. Internal consistency for both positive and negative affect in our sample was excellent, with McDonald's ω_{PA}=0.93, ω_{NA}=0.92.

Ratings of perceived boredom and exertion

Attached to the PANAS questionnaire, boredom (i.e., item “bored”) and state exertion (i.e., item “exerted”) were measured using single items that participants rated. Accordingly, the answers were given on the same 5-point Likert-type scale as the PANAS, ranging from (1) “not at all” to (5) “extremely”.

The game to play: Tetris

To create different situational contexts in which the participants had to exert effort, we utilized playing Tetris (https://www.gamesbasis.com/games/classic/tetris/, January 2022). Tetris has proven to be suitable for the research context (Milyavskaya et al., 2021), especially for our research purpose. First, it can be designated as a serious or an entertainment game by highlighting different aspects of the game in its introduction to the participants. Tetris is a world-famous entertainment game and thereby quite easily introduced as such. On the other hand, it can also be introduced as a learning game, as Tetris requires concentration, mental rotation, and spatial imagination to be successful (De Lisi & Wolford, 2002). Second, Tetris requires continuous attention and focus to succeed, and these factors have proven to demand a certain amount of effort (Bieleke et al., 2021; Kahneman, 1973). Further, as this study was conducted online, the threshold to play should be low so that the participants were less tempted not to follow the study instructions. Thus, we used a free-of-charge browser-based version of Tetris, for which participants did not need to register or download any software. Fourthly, Tetris is relatively simple to understand, so short and quick instructions are sufficient for a successful game, even for people who have little or no experience with Tetris.

Introduction to Tetris: task framing

We experimentally induced the context of the game (i.e., entertainment or learning) by using different introductions when asking participants to play the game (instructional framing), which has been used in previous studies (e.g., Steiger & Kühberger, 2018). Using these different introductions, we aimed to elicit different attitudes and expectations in the participants, influencing the experience of effort. For introducing Tetris as an entertainment game, participants received instructions, emphasizing recreational elements, relaxation, and joy. Whereas for the learning task framing, Tetris was introduced as a serious game and its learning, concentration, and performance elements were highlighted (see SI 1 in OSF: https://osf.io/g9mw4).

Data analysis

We conducted all data analyses using R version 4.3.1 (R Core Team, 2023) and Mplus version 8.1 (Muthén & Muthén, 1998–2017). The R Script and Data can be obtained in OSF (https://osf.io/g9mw4). For the data wrangling, we employed the package *tidyverse* version 2.0.0 (Wickham et al., 2019), and for calculating the questionnaire properties, the package *misty* version 0.4.12 (Yanagida, 2024). Further, we performed a latent profile analysis (LPA) using the package *tidyLPA* version 1.1.0 (Rosenberg et al., 2018).[1] The three pairs of items of the roles of effort for self-regulation demonstrated excellent internal consistency, suggesting that the items within each pair measure the same underlying construct. For this reason, we used the mean scores of the item pairs as indicators in the LPA rather than including individual items. This approach avoids redundancy, limits unnecessary complexity, and prevents the formation of overly fine-grained profiles (Nielsen et al., 2016).

To examine post hoc associations between latent profiles and outcome variables, the Bolck, Croons, and Hagenaars (BCH) method (Asparouhov & Muthén, 2014; Bolck et al., 2004) was applied in Mplus (Muthén & Muthén, 1998–2017), as it outperforms other methods (Nylund-Gibson et al., 2019). The BCH method allows for mean comparisons across latent profiles while appropriately accounting for uncertainty in class assignment, which improves the robustness of post hoc results compared to analyses based on modal class assignment. We tested differences between latent profiles on the dependent variables positive and negative affect, exertion, and boredom. Additionally, task framing (serious vs. entertainment) was included as a moderator to examine potential interaction effects with profile membership. We used a manual two-step approach: For this purpose, we replicated the LPA solution in Mplus and saved the BCH weights in the first step. In the second step, the BCH-based regression analyses were conducted in Mplus based on the BCH weights.

Furthermore, differences in the categorical outcomes of play time and willingness to exert further effort across the latent classes were examined using separate BCH Step-2 approaches in Mplus. BCH weights, derived from a prior LPA, were included to account for classification uncertainty. Mixture models were estimated using the robust maximum likelihood estimator (MLR).

Results

Descriptive statistics

Participants reported playing video games for $M=398$ (± 745) minutes per week. 63% of the participants were very familiar, 26% were somewhat familiar, and 11% were not familiar with Tetris before our study. During our experiment, 70% of participants reported playing Tetris for the intended duration of ten minutes or even longer. 26% of the participants reported having played for five to ten minutes, whereas 4% for five minutes or shorter. In total, 82% of the participants refused to play another game of Tetris after finishing the study. The descriptive statistics of the central measures of this study and their correlations are presented in Table 2. We found high correlations between the roles of effort. Furthermore, all roles of effort show a moderate relation with positive affect and small correlations with exertion. The roles of effort show a small negative relation to boredom and no significant relation to negative affect.

Manipulation check

Of the $n=211$ participants who received the serious framing, 33% indicated that they understood Tetris to be a learning game (i.e., a serious game), whereas 67% perceived it as an entertainment game. Of the $n=260$ individuals in the entertainment framing, 10% indicated that they see Tetris as a learning game, and 90% as an entertainment game. A χ^2-test indicated a significant relationship between framing and perception of Tetris, $\chi^2(1)=37.00$, $p<.001$, $\varphi=0.28$, with an odds ratio of 4.28 (95%- CI 2.62, 7.00). The probability of perceiving Tetris as a learning game was 3.3 times higher

[1] Additional analyses revealed that gender does not predict profile membership and that the roles of effort are measured equivalently across gender. Further analyses revealed that individuals with low familiarity with Tetris were significantly more likely to belong to the low-effort profile. However, the main findings remained robust when controlling for prior familiarity with the game. See SI3 on OSF for the complete results.

Table 2 Means, standard deviations, and correlations of the roles of effort and the state measures

Measure	Mean	SD	INS	REW	ADD	PA	NA	Bore.	Exer.
INS	4.77	1.44	-						
REW	4.77	1.52	0.77	-					
ADD	4.91	1.52	0.84	0.82	-				
PA	2.97	0.97	0.47	0.49	0.46	-			
NA	1.41	0.69	$-.03_{n.s.}$	$-.07_{n.s.}$	$-.06_{n.s.}$	$0.01_{n.s.}$	-		
Bore.	1.58	1.00	−0.30	−0.28	−0.29	−0.30	0.47	-	
Exer.	2.69	1.10	0.22	0.19	0.21	0.33	0.28	$-0.01_{n.s.}$	-

SD = standard deviation; INS = effort-as-instrument, REW = effort-as-reward, ADD = effort-adding-value; PA = positive affect, NA = negative affect; Bore. = perceived boredom, Exer. = perceived exertion; INS, REW, and ADD were measured before, and PA, NA, Bore., and Exer. were measured after playing Tetris. All correlations are significant with $p<.001$ if not otherwise specified; n.s. = non-significant

when receiving the serious framing than when receiving the entertainment framing.

To test for measurement invariance across the framing conditions, a confirmatory factor analysis was conducted (configural, metric, scalar invariance) using robust maximum likelihood estimation (MLR). Model comparisons revealed no significant loss of fit between models ($\Delta\chi^2(5)=5.08$, $p=.406$ for metric, $\Delta\chi^2(5)=3.31$, $p=.653$ for scalar). Furthermore, changes in fit indices were within recommended thresholds (metric model: $\Delta CFI=0.000$, $\Delta RMSEA = -0.018$, $\Delta SRMR=0.009$; scalar model, $\Delta CFI=0.001$, $\Delta RMSEA = -0.014$, $\Delta SRMR=0.001$). This suggests that the roles of effort scale can be considered invariant and comparable across framing conditions.

Latent profiles of the roles of effort for self-regulation

A latent profile analysis was performed to group individuals into classes based on their constellation of the three roles of effort for self-regulation (instrument, reward, adding-value). We estimated a series of latent profile models that differed in their assumptions about the variances and covariances of the profile indicators. Model 1 assumed equal variances across profiles and fixed all covariances to zero. Model 2 allowed the variances to vary between profiles while keeping covariances fixed to zero. Model 3 assumed equal variances and equal covariances across profiles, whereas Model 6 allowed both variances and covariances to vary freely. Models 4 and 5 could not be estimated due to structural limitations of the underlying mclust package, which does not support model specification involving varying variances with equal covariances (Model 4), or equal variances with varying covariances (Model 5) (Scrucca et al., 2016). The fit statistics for the possible profile structures are displayed in Table 3. Using AIC, AWE, BIC, CLC, and KIC as fit indices (Akogul & Erisoglu, 2017), an analytic hierarchy process favored a solution with four latent classes and equal variances and covariances (Model 3). This solution exhibits superior model fit as evidenced by lower AIC, AWE, BIC, CLC, and KIC values in comparison with models one, two, and six. The significant BLRT p-value further indicates an improvement in model estimation in comparison with only three latent profiles (Model 3). Further, the elbow plot for Model 3 indicates that adding more than four classes does not yield a substantial improvement in model fit that would justify the increased complexity (Fig. 2). An entropy of 0.879 indicates a high fit of the data and a good distinction between the latent profiles.

As depicted in Fig. 3 (blue), class one represents the high-effort group, characterized by above-average scores on all three roles of effort ($M_{instrument}$ = 5.37 ± 0.87, M_{reward} = 5.46 ± 0.92, M_{adding} = 5.50 ± 0.99). Class two represents the low-effort group characterized by below-average scores on the scales for all effort roles in gaming (orange; $M_{instrument}$ = 1.95 ± 0.79, M_{reward} = 1.92 ± 0.81, M_{adding} = 2.04 ± 0.98). Although classes three (instrumentality-effort) and four (reward-effort) both understand effort as adding value to an outcome, they differ in the other two roles. Class three has a higher score on instrumentality rather than effort-as-reward (pink; $M_{instrument}$ = 5.05 ± 0.90, M_{reward} = 3.44 ± 0.88, M_{adding} = 4.39 ± 1.30). This is reversed for class four (green; $M_{instrument}$ = 3.15 ± 0.74, M_{reward} = 5.29 ± 0.99, M_{adding} = 4.82 ± 1.19). The four profiles differ in the number of assigned participants. The high-effort is the largest class with 318 individuals (67% of the sample), then the instrumentality-effort with 64 individuals (14%), the low-effort profile with 53 participants (11%), and the smallest class, the reward-effort, with 36 individuals (8% of the sample). The substantial size of the high-effort profile may account for the strong correlation among the effort roles. However, classification accuracy across all profiles was high. Participants in the first class (high-effort) were classified as such with 95.3% probability, in the second class (low-effort) with 91.9%, in the third class (instrumentality-effort) with 85.3%, and in the fourth class (reward-effort) with 95.7% probability.

Table 3 Fit statistics for the possible profile structures

Model	Classes	AIC	AWE	BIC	CLC	KIC	Entropy	BLRT *p*	%
1	1	4018.92	4096.78	4043.85	4009.92	4027.92	1	-	100
1	2	3333.16	3464.39	3374.71	3315.02	3346.16	0.932	0.010	17
1	3	2981.00	3165.61	3039.16	2954.71	2998.00	0.860	0.010	10
1	4	2853.06	3090.93	2927.85	2818.77	2874.06	0.854	0.010	8
1	5	2836.13	3127.19	2927.54	2793.89	2861.13	0.880	0.010	2
1	6	2782.35	3126.69	2890.38	2732.07	2811.35	0.859	0.010	4
2	1	4018.92	4096.78	4043.85	4008.92	4027.92	1	-	100
2	2	3321.73	3493.15	3375.74	3297.33	3337.73	0.801	0.010	38
2	3	2918.23	3182.63	3001.33	2880.03	2941.23	0.898	0.010	8
2	4	2806.91	3164.64	2919.09	2754.54	2836.91	0.816	0.010	8
2	5	2805.03	3255.92	2946.29	2738.67	2842.03	0.820	0.079	6
2	6	-	-	-	-	-	-	-	-
3	1	2891.64	3009.43	2929.04	2875.64	2903.64	1	-	100
3	2	2797.28	2968.56	2851.26	2773.04	2813.28	0.875	0.010	18
3	3	2774.58	2999.28	2845.22	2742.15	2794.58	0.785	0.010	9
3	4	**2671.48**	**2949.23**	**2758.73**	**2631.24**	**2695.48**	**0.879**	**0.010**	**8**
3	5	2668.39	2999.57	2772.27	2619.96	2696.40	0.783	0.050	8
3	6	2676.30	3060.78	2796.79	2619.80	2708.30	0.750	0.812	8
6	1	2891.64	3009.43	2929.04	2875.64	2903.64	1	-	100
6	2	2706.07	2957.83	2785.01	2669.19	2728.07	0.562	0.010	44
6	3	-	-	-	-	-	-	-	-
6	4	-	-	-	-	-	-	-	-
6	5	-	-	-	-	-	-	-	-
6	6	-	-	-	-	-	-	-	-

The favored solution is highlighted in bold. Model 1 = equal variances and covariances fixed to 0; Model 2 = varying variances and covariances fixed to 0; Model 3 = equal variances and covariances; Model 4 = varying variances and equal covariances; Model 5 = equal variances and varying covariances; Model 6 = varying variances and covariances. Models 4 and 5, as defined in tidyLPA, could not be estimated due to structural limitations of the underlying mclust package, which does not support model specifications with varying variances and equal covariances (Model 4) or equal variances and varying covariances (Model 5) (Scrucca et al., 2016); For Model 6 the 3 and 4 profile solutions could not be estimated; *AIC* = Akaike Information Criterion, *AWE* = Approximate Weight of Evidence, *BIC* = Bayesian Information Criterion, *CLC* = Classification Likelihood Criterion, *KIC* = Kullback Information Criterion, *BLRT* = bootstrapped likelihood ratio test; If below 0.05, the model with k_0 latent classes demonstrates a significantly better fit than a model with (k-1) latent classes. Higher entropy values (Range 0–1) indicate better classification of individuals to the latent class. % = % of the smallest class of the total sample

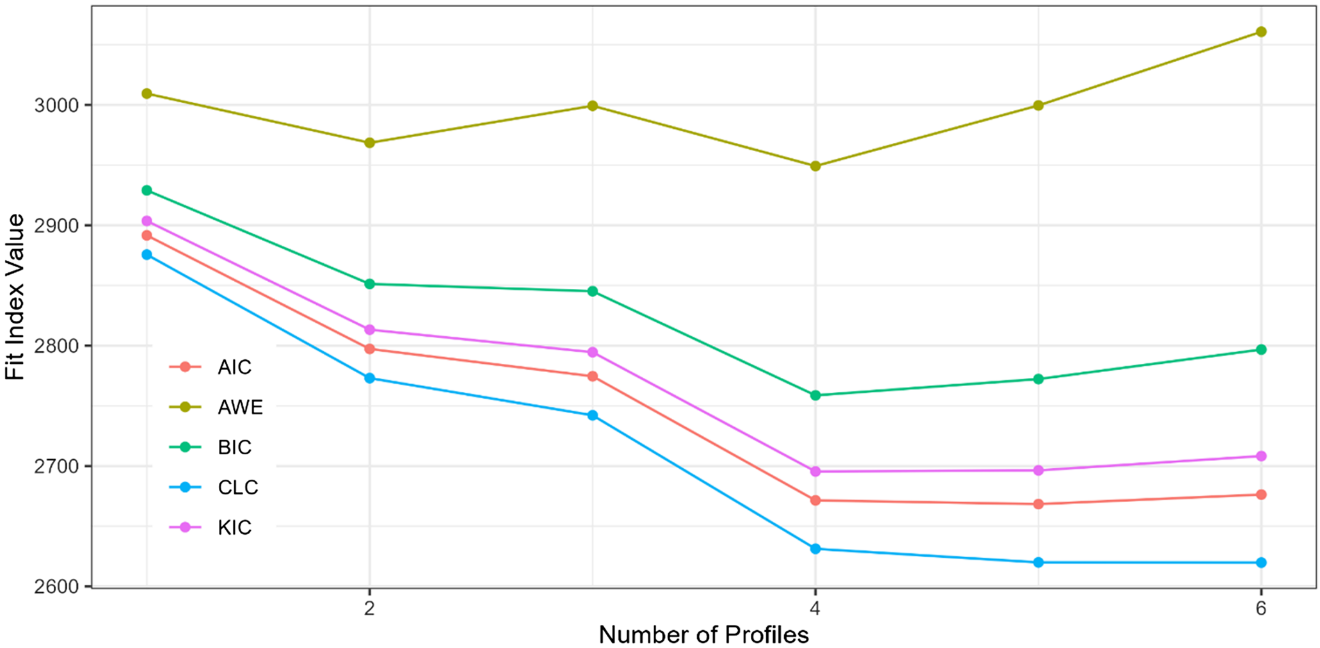
Association of effort profiles, task framing, and game experience (in Mplus)

We used the BCH method to examine differences in positive and negative affect, boredom, and exertion after the game across different effort profiles (high-effort, low-effort, instrumentality-effort, reward-effort) and framing conditions (entertainment, serious). Figure 4 displays the means, standard deviations, and distributions of the dependent variables per profile for each framing condition (calculated in R).

Post-hoc comparisons using the BCH method in Mplus revealed that participants in the low-effort profile reported significantly lower positive affect than those in the high-effort (ΔM = −1.24, SE = 0.14, p < .001), instrumentality-effort (ΔM = −0.83, SE = 0.18, p < .001), and reward-effort profiles (ΔM = −0.91, SE = 0.20, p < .001). Furthermore, participants in the high-effort profile showed significantly higher positive affect than those in the instrumentality-effort (ΔM = −0.41, SE = 0.14, p = .003) and reward-effort profiles (ΔM = −0.33, SE = 0.17, p = .047). No significant framing effects for positive affect were observed within any of the four profiles (all ps > 0.144) (see Fig. 4A).

For negative affect, participants in the reward-effort profile reported less negative affect than those in the instrumentality-effort profile (ΔM = −0.28, SE = 0.14, p = .048). Additionally, there was a significant effect of task framing in the low-effort profile, with lower negative affect in the serious compared to the entertainment framing (b = −0.34, SE = 0.14, p = .017). No significant framing effects for negative affect were found in the other profiles (all ps > 0.087) (see Fig. 4B).

For boredom, participants in the low-effort profile reported significantly higher values than those in the high-effort (ΔM = 1.04, SE = 0.22, p < .001), instrumentality-effort (ΔM = 0.79, SE = 0.26, p = .003), and reward-effort profiles (ΔM = 0.75, SE = 0.27, p = .006). No significant framing effects on boredom were observed within any of the four profiles (all ps > 0.064) (see Fig. 4C).



Note: AIC = Akaike Information Criterion; AWE = Approximate Weight of Evidence; BIC = Bayesian Information Criterion; CLC = Classification Likelihood Criterion; KIC = Kullback Information Criterion; The plot shows diminished improvements in fit after the four-class solution, supporting the selection of the solution with four latent profiles.

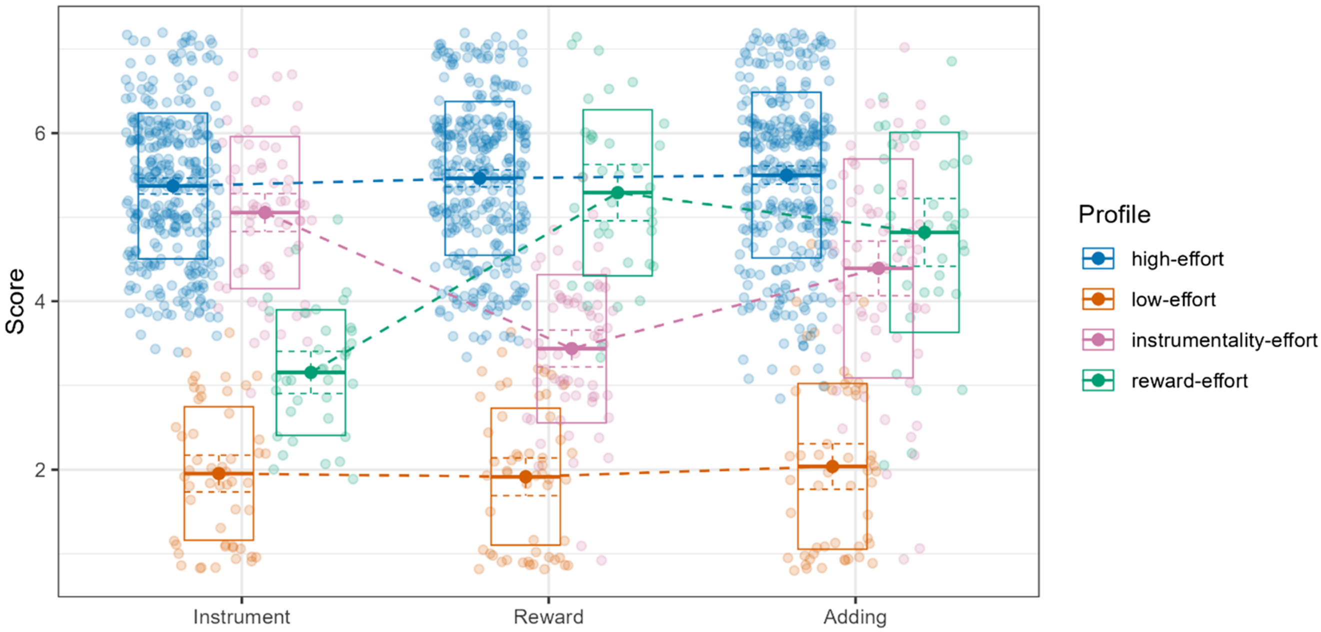
Fig. 2 Elbow plot illustrating model fit for the estimation of 1- to 6-profile solutions for Model 3 (equal variances and covariances)

Participants in the low-effort profile reported significantly lower exertion than those in the high-effort (ΔM = −0.63, SE = 0.16, p < .001) and instrumentality-effort profiles (ΔM = −0.63, SE = 0.20, p = .002). Similarly, participants in the reward-effort profile reported lower exertion than those in the high-effort (ΔM = −0.50, SE = 0.21, p = .016) and instrumentality-effort profiles (ΔM = −0.50, SE = 0.24, p = .037). Additionally, there was a significant effect of task framing in the low-effort profile, with lower RPE in the serious compared to the entertainment framing (b = −0.86, SE = 0.28, p = .002). No significant framing effects were found in the other profiles (all ps > 0.20) (see Fig. 4D).

Association of effort profiles and behavior

We further investigated whether individuals across the four effort profiles differed in their behavior. The indicated play times of Tetris per profile can be found in Table 4 (the playing time was divided into < 10 and ≥ 10 min for the analysis). The profiles differed in their play time, with the longest for the reward-effort (78% playing ≥ 10 min) and high-effort profiles (71% playing ≥ 10 min), followed by the instrumentality-effort (70% playing ≥ 10 min) and low-effort profiles (55% playing ≥ 10 min). A significant difference in play time was only found between the low-effort and reward-effort profiles (OR = 0.34, 95%-CI 0.123, 0.962).

Regarding the free choice to exert further effort in another round of Tetris, 23% of participants belonging to the high-effort profile, 19% of the reward-effort, 9% of the instrumentality-effort, and none of the low-effort group indicated that they wanted to play again. Odds ratios (OR) indicated that the individuals in the high-effort profile were 3.03 (95%-CI 0.101, 1.078) times more likely to play again than those in the instrumentality-effort profile. Similarly, individuals in the reward-effort profile were 2.41 (95%-CI 0.590, 9.843) times more likely to choose to play again compared to the instrumentality-effort profile. However, neither OR was statistically significant.



Note*:* Instrument = effort-as-instrument, Reward = effort-as-reward, Adding = effort- as-adding-value. Answers were given on a 7-point Likert-type scale ranging from (1) “strongly disagree” to (7) “strongly agree”.

Fig. 3 The selected profile solution according to AIC, AWE, BIC, CLC, and KIC with equal variances and covariances (Model 3) with four latent profiles

Discussion

This study is the first to identify distinct profiles of roles of effort for self-regulation and how these profiles differ in experiencing cognitive effort. A latent profile analysis identified four profiles (high-effort, low-effort, instrumentality-effort, reward-effort) differing regarding the three roles of effort (instrument, reward, value-added). While people belonging to the high-effort profile rated all three roles highly, people in the low-effort profile indicated that exerting effort lacked any personal relevance. The instrumentality-effort and the reward-effort profiles both valued effort, but for different reasons. The former saw it as a means to an end, the latter as inherently rewarding.

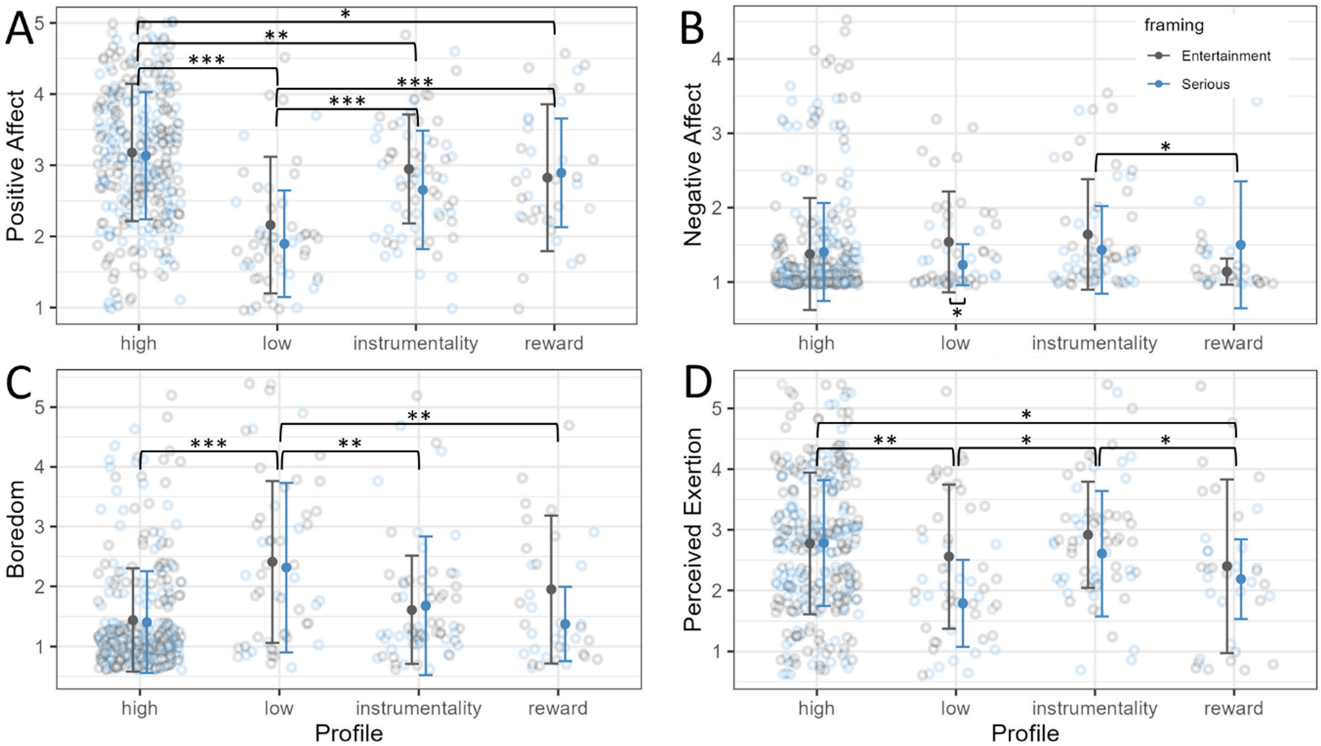
These findings align with recent work indicating that individual differences in cognitive effort allocation can be attributed to several underlying factors, such as reward sensitivity and instrumentality (Musslick et al., 2019) or – as our study highlights – distinct effort roles reflected in effort profiles. This is consistent with recent theorizing emphasizing that effort can simultaneously have multiple roles (Inzlicht et al., 2018). Our study extends this line of research by empirically demonstrating that individual differences in role configuration give rise to distinct effort profiles.

Effort experience and willingness to exert effort

Willingness to exert effort

Importantly, we found differences between the effort profiles in the willingness to participate in a subsequent cognitive effort task. As expected, the high-effort profile showed the greatest willingness to participate, and no one belonging to the low-effort profile wanted to play a further cognitively effortful game. Interestingly, the reward-effort profile had a two times greater willingness to invest further effort in the subsequent game than the instrumentality-effort profile.

These findings align closely with the predictions derived from the EVC theory (Shenhav et al., 2013). Specifically, the results suggest that the more roles effort fulfills, the higher the overall expected value (EV) of exerting effort. This, in turn, increases the willingness to engage in effortful tasks. Reflected, for instance, in the reward-effort and



Note*:* Values are presented based on the most likely profile assignment, according to the LPA results from R. Significance levels were computed in Mplus and are indicated accordingly. The Effort profiles are displayed on the x-axis: high = high-effort, low = low-effort, instrumentality = instrumentality-effort, reward = reward-effort. Answers were given on a 5-point Likert-type scale. Colors indicate task framing. Error bars represent the standard deviation. Raw data points in the background. * p < .05, ** p < .01, *** p < .001.

Fig. 4 The mean and standard deviation of (**A**) positive affect, (**B**) negative affect, (**C**) boredom, and (**D**) perceived exertion per effort profile, separately for the experimental conditions

Table 4 Indicated play times of Tetris per profile

Profile	< 5 min	5–10 min	10 min	> 10 min
High-effort	4%	25%	39%	32%
Low-effort	6%	38%	43%	13%
Instrumentality-effort	3%	27%	33%	38%
Reward-effort	0%	22%	36%	42%

Participants were intended to play for 10 min. Answers were given according to the categories used in the table

high-effort profiles, showing a greater willingness to continue the task. These profiles represent individuals for whom effort holds value beyond merely achieving an external outcome. On the other hand, the EVC theory predicts that when the subjective costs of effort outweigh its expected benefits, individuals are less willing to exert effort, as reflected in the low-effort profile.

Affect and boredom

Further, the four profiles differed in how effort was experienced during the task (i.e., negative and positive affect and boredom). People belonging to the low-effort profile reported the most negative experiences, characterized by reduced positive affect and heightened boredom. In contrast, those in the high-effort profile reported more positive affect than all other profiles.

This pattern aligns with prior research indicating that value and meaning enhance task experience (van Tilburg &

Igou, 2017). It also resonates with findings that boredom tends to emerge in tasks perceived as low in value (Pekrun, 2006) and is understood as a call to action to the bored individual (Wolff, Radtke et al., 2024). Thus, when effort is not perceived as valuable in any of its roles, as in the low-effort profile, but still must be exerted, the task is experienced as more aversive with a more negative affect and greater boredom compared to individuals for whom effort has any role.

Taken together, these findings illustrate how the combination of different effort roles is associated not only with the willingness to engage in effortful tasks but also with how effort is experienced. This helps explain why some individuals perceive effortful tasks as meaningful and rewarding and derive satisfaction from participating, while others experience them as aversive – differences that can significantly impact performance and success in the long run (Duckworth et al., 2007; Wolff et al., 2024). These insights hold valuable implications for applied contexts. For example, perceiving effort not merely as instrumental but also as inherently rewarding may be associated with reduced boredom and greater persistence in education or workplace settings.

Perceived exertion

The findings regarding perceived exertion (RPE) are particularly noteworthy. Both the high-effort and the instrumentality-effort profiles reported higher perceived exertion than the low-effort and the reward-effort profiles. Interestingly, however, the reward-effort profile did not differ from the low-effort profile in perceived exertion, despite showing a greater willingness to engage in the task, a better task experience, and a longer play time. Thus, these findings raise the question of whether the observed differences in perceived exertion reflect actual differences in effort investment or rather differences in how exerting the task is subjectively experienced (Steele, 2020). Unfortunately, the Tetris version used in this study did not allow for reliable performance measurement, which limits the ability to directly test this. Future studies should build upon our findings and additionally measure performance to investigate whether the differences in perceived exertion are reflected in differences in performance as well.

Based on recent studies, we would tentatively speculate that the low exertion score among reward-effort is not due to a low level of exerted effort, but that this group perceives it as less tiring to exert themselves in games (Milyavskaya et al., 2021; Song et al., 2019; Steele, 2020). This interpretation is supported by the behavioral choice data: While none of the participants in the low-effort profile (who also reported low RPE values) wanted to play again, twice as many participants in the reward-effort profile agreed to play again compared to those in the instrumentality-effort profile. Additionally, the individuals belonging to the reward-effort profile reported the longest play time for all effort profiles and a significantly longer play time than the low-effort profile. These findings are in line with the idea that individuals belonging to the reward-effort profile perceived effort as less exerting than the other effort profiles. This interpretation would suggest that seeing effort as inherently rewarding may buffer against the experience of exertion. Consequently, fostering perceptions of effort as inherently rewarding, for example, by emphasizing mastery or the enjoyment of challenge, could serve as an effective strategy to promote sustained engagement while reducing perceived exertion. However, future studies should investigate the perception of exertion between the effort profiles in greater depth.

Framing and task context

Furthermore, our findings indicate that framing the game either as an entertainment or a serious game can influence task experience differently across effort profiles. Specifically, for individuals with low valuation of effort, a serious task framing appears to enhance task experience. One possible explanation is that when a task lacks subjective value and is framed as purely for fun, it may be experienced as less meaningful or engaging. In contrast, when the task is associated with a positive external purpose, this may improve the subjective experience. However, our study design does not fully permit a rigorous test of interaction effects between framing and effort profiles, as the framing manipulation was applied at the beginning of the study before effort profiles were assessed. Nonetheless, the latent profile structure proved invariant across framing conditions, indicating that framing did not substantially affect profile formation. However, future studies could address this limitation by assessing effort profiles before introducing the framing manipulation to more robustly examine potential interaction effects.

Finally, our results raise intriguing questions for future research, such as whether the profiles of effort roles vary depending on the context (e.g., sports, work, etc.), or whether they might even be specific for each task. To illustrate, the same person might have different effort profiles for learning a new language or learning chemistry. Although theorizing suggests that the value-generating roles of effort (reward, value-adding) generalize between different domains (Eisenberger, 1992), empirical research reports mixed findings (e.g., Wolff et al., 2024; for a review, see Stähler et al., 2025). Thus, future research should investigate the generalization of effort profiles within and between domains.

Limitations

While this study offers novel insights, we would like to acknowledge certain limitations. Although our study included a substantial number of participants, we also observed a relatively high drop-out rate, with approximately 21% of individuals who initially registered for the study not completing it. At first glance, this might appear significant, particularly given the study's focus on motivation to perform a task, raising potential concerns about selection and survivorship bias, which could influence our findings (Sammut et al., 2021). However, a closer examination of the data reveals that 71 of the 130 participants who dropped out never progressed beyond the initial study page and did not engage with the study itself. This suggests that their dropout likely reflects a lack of initial commitment rather than issues related to the study design or content. Thus, the remaining drop-out rate of 9% is within an acceptable range for online studies. Furthermore, the drop-out rate after receiving the framing was not influenced by the framing condition, suggesting that the conditions did not introduce any selection bias.

Secondly, it is important to acknowledge that some of our findings are correlational and rely on self-reported data. This methodological limitation restricts the ability to draw causal conclusions and necessitates caution when interpreting the observed relationships. Self-report measures are inherently vulnerable to biases, such as social desirability, recall inaccuracies, and individual differences in introspective ability (Nisbett & Wilson, 1977; Schwarz, 1999). These factors can potentially distort participants' reports of their motivation and task experience. However, the present study specifically focused on the subjective perception and experience of effort, constructs that are, by definition, internal and best captured through self-reports. Moreover, meta-analytic evidence supports the validity of such measures by showing meaningful correlations with more objective measures (e.g., Chen et al., 2002; Lea et al., 2022). Thus, our findings on perceived exertion, for example, may offer indirect indications of actual effort exertion. However, the present research questions should be further explored in controlled laboratory settings, where objective measures of performance and effort, such as heart rate, can complement self-reported data (Åstrand, 1965; Åstrand & Ryhming, 1954).

Additionally, in the present study, we assessed effort-related affect in a rather general manner, focusing on positive and negative affect and boredom. Future studies could build on this by examining the affective experience of effort in greater detail, for instance by differentiating between discrete affective states such as frustration, pride, or interest, and exploring how these are differentially associated with the identified effort profiles.

Further, it should be noted that we used Tetris, a widely known and familiar game, for the framing manipulation. For participants with prior experience with Tetris, it may have been difficult to convincingly reframe Tetris as a learning game. Future research should therefore further explore the influence of contextual framing, specifically learning versus entertainment, on effort profiles and task experience. To better capture potential framing effects, subsequent studies could employ novel or less familiar tasks, which may be more effective in activating distinct contextual mindsets.

Lastly, the generalizability of our findings may be limited, as our sample was recruited via Amazon MTurk during a period when COVID restrictions prevented on-site data collection. Thus, our participants are likely to be more digitally literate, have higher levels of education, and are based in the United States (Huff & Tingley, 2015; Munger et al., 2023). As a result, our sample may not fully represent broader or more diverse populations in terms of cultural background, educational attainment, or familiarity with digital tasks such as gaming. These factors could influence how effort is perceived and experienced, particularly in a technology-mediated context like the one used in this study. This may place certain limits on the extent to which the findings generalize to other populations, especially those with differing cultural norms around effort, varying access to digital technologies, or alternative motivational contexts. Future research should aim to replicate the current findings with more diverse and representative samples to better assess their cross-cultural and cross-contextual applicability.

Conclusion

The present study supports the idea that different roles of effort for self-regulation (instrument, reward, value-adding) contribute to its overall valuation simultaneously. This is displayed in four latent profiles (high-effort, low-effort, instrumentality-effort, reward-effort), indicating different constellations of effort roles in the context of a cognitive gaming task. Crucially, these effort profiles were not only linked to how individuals experienced effort, reflected in positive and negative affect, boredom, and perceived exertion, but also to their willingness to engage in future effortful tasks. However, concerning the task experience, the specific role of effort appeared to be of less importance compared to effort having a role at all. In contrast, regarding future behavior, our findings suggest that valuing the inherent reward of effort might be a more decisive factor than valuing its instrumentality. This highlights a promising direction for both theory and practice: fostering the inherent valuation of effort may be key to sustaining self-regulation and promoting persistent engagement in demanding tasks.

Future research could build on these insights to explore how interventions or learning environments might cultivate more positive effort beliefs, ultimately enhancing motivation and performance. Overall, this study advances our understanding of the multifaceted nature of effort in self-regulation and opens new avenues for investigating how effort roles shape both experience and behavior.

Author contributions Conceptualization: Johanna Stähler, Wanja Wolff, Maik Bieleke, Julia Schüler; Methodology: Johanna Stähler, Wanja Wolff, Maik Bieleke, Julia Schüler; Software: Johanna Stähler; Formal analysis and investigation: Johanna Stähler; Data curation and visualization: Johanna Stähler; Writing – original draft preparation: Johanna Stähler; Writing – rewriting and editing: Johanna Stähler; Wanja Wolff, Maik Bieleke, Julia Schüler; Funding acquisition: Julia Schüler; Resources: Julia Schüler; Supervision: Julia Schüler.

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Data availability All Data and Code are available in the OSF and can be accessed using the following link: https://osf.io/g9mw4.

Declarations

Competing interests The authors have no competing interests to declare that are relevant to the content of this article.

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