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Towards a more individualised support of science competition participants – identification and examination of participant profiles based on cognitive and affective characteristics

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ABSTRACT

Science competitions target students interested in science with the aim to support them in developing science competence and career aspirations. Contrary to the common belief that science competition participants are exceptionally competent and strongly motivated to pursue a science career, there is growing evidence that the entirety of participants is rather heterogeneous in terms of their cognitive and affective characteristics. For science competitions to better support all participants in developing competence and career aspirations, a better understanding of the cognitive and affective characteristics of the entirety of participants is required. This study examined the Physics Olympiad as a specific type of science competitions, leading to a nuanced characterisation of $N = 155$ Physics Olympiad participants. Latent profile analyses revealed four participant profiles distinguished by specific patterns in cognitive abilities, physics interest, and physics self-efficacy. Profiles differed in their performance in the competition and their physics career aspiration. Grade level, gender, previous participation in the competition, and teacher support explained differences in profile membership. Our findings emphasise that Physics Olympiad participants are a heterogeneous group with varying needs and offer implications for more individualised support activities to better support the entirety of participants in developing science competence and career aspirations.

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Introduction

One central aim of science education is to support students in developing competence and engagement in science, potentially preparing them for a science career. In order to best

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support the development of science competence and engagement, students must be offered learning activities designed to meet their individual needs (e.g. Smale-Jacobse et al., 2019; U. S. Department of Education, 2013). One example of such learning activities are science competitions heavily subsidised by governments all around the world (e.g. Stake & Mares, 2001). Science competitions target students interested in science with the aim to support them in the development of their competence and to nurture their interest, effectively engaging them in a science career. Contrary to the common belief that science competition participants are all exceptionally competent and strongly motivated to pursue a science career, there is a growing body of evidence indicating that the entirety of science competition participants is rather heterogeneous in terms of cognitive (e.g. Urhahne et al., 2012) and affective characteristics (e.g. Steegh et al., 2021a). In order to better support all science competition participants in developing science competence and career aspirations, a better understanding of the diverse cognitive and affective characteristics of the entirety of participants is required.

Previous research provides a rather incomplete picture of science competition participant characteristics, their science competence and career aspirations. First, studies mainly focussed on the small proportion of more successful participants. Second, the focus was either on cognitive student characteristics (e.g. Köhler, 2017) or affective (e.g. Steegh et al., 2021a) although both were shown to play an important role in the development of science competence and career aspirations (e.g. Deary et al., 2007; Marsh & Martin, 2011). Third, most studies investigated relationships between single student characteristics and science competence or career aspirations (e.g. Urhahne et al., 2012). However, as suggested by Teig et al. (2020), due to the high interrelatedness of student characteristics, insights on the effects of single characteristics on science competence or career aspiration offer little guidance for designing learning activities tailored to students' needs. Hence, to better support a broad range of science competition participants in developing science competence and career aspiration, taking a holistic approach in which cognitive and affective characteristics and their relationships with science competence and career aspirations are studied as interrelating factors should be expedient.

The main goal of this study was to develop a differentiated characterisation of participants of the German Physics Olympiad as a task-centred science competition. We employed a holistic approach by identifying profiles of participant characteristics, i.e. patterns of cognitive and affective characteristics unique to selected groups of participants. We moreover examined how profile membership relates to science competence and career aspirations and the role of selected covariates on facilitating or hindering favourable transitions of participants between profiles. Our findings provide implications for more individualised and targeted support activities to best support all science competition participants in developing their science competence and career aspirations.

Theoretical background

Formats of science competitions

Science competitions are competitive informal learning activities that come in a broad range of formats, typically focusing on school science subjects. These competitions commonly share the broader objective of supporting participating students in developing competence in science and nurturing their motivation to possibly engage in a science career (e.g. Campbell et al., 2000; Petersen et al., 2017). Science competitions can be broadly categorised into project-centred competitions, such as science fairs, and task-centred competitions, such as science Olympiads, although hybrid and alternative formats exist. In project-centred competitions, such as the renowned Regeneron International Science and Engineering Fair, participants either work individually or in teams on self-selected projects, thereby applying scientific methodologies to investigate a research problem (e.g. Jaworski, 2013). In contrast, task-centred competitions typically require participants to work individually on demanding theoretical and often also experimental problems (Petersen & Wulff, 2017). Examples of task-centred competitions include Olympiads such as the International Olympiads in Biology, Chemistry, and Physics as well as the International Junior Science Olympiad, in which exceptionally motivated and skilled students from around the globe participate. These participants are usually selected through national multi-round Olympiads which encompass a far greater range of students. Throughout these multi-round Olympiads, participating students solve progressively difficult subject-specific problems. Only the highest-performing participants advance to the subsequent rounds. Beyond simply identifying the most exceptional participants, these competitions also typically offer support activities, such as seminars, excursions, lectures, and learning materials, to further support the development of participants' science competence and career aspirations. However, it is important to note that the extent of support provided tends to increase in the more advanced competition rounds. This implies that the more successful participants receive the greatest support, while the majority of participants, who are less successful, receive comparatively less support.

The German Physics Olympiad as a science Olympiad

The German Physics Olympiad serves as the national precursor to the International Physics Olympiad. At the start of this competition, advertisement material is sent out to secondary schools across Germany. Interested students then have the option to voluntarily register online for participation, i.e. participating students represent a self-selected group. The Physics Olympiad comprises four distinct rounds, each presenting participants with demanding theoretical and experimental physics problems that they have to work on individually. Only the highest-performing participants from one round advance to the subsequent round. In the first and second round, participants work on the problems either at home or in school. About five months are available for solving the first-round problems, whereas approximately one month is designated for the second-round problems. The third and fourth round brings participants together at a research institute for a week of intense engagement, involving both experimental and theoretical examinations. During this week, participants also have the opportunity to attend seminars, excursions, and talks by physicists. The top five performers of the fourth round then earn an invitation to participate in the International Physics Olympiad. Overall, support activities at the outset of the Physics Olympiad are somewhat limited, primarily relying on the provision of online learning resources. However, as participants progress to later rounds, support activities become more variable and lively, featuring elements such as seminars and excursions, due to the in-person character of these rounds. For a detailed breakdown of the German Physics Olympiad, see Petersen and Wulff (2017).

We argue that the German Physics Olympiad exhibits characteristics that make it a prototype among science Olympiads in certain aspects. A survey among countries participating in the International Physics Olympiad revealed that there are both similarities and differences among countries' national Physics Olympiads (Petersen & Wulff, 2017). On average, national Physics Olympiads comprise 3.1 rounds ($SD = 1.2$ rounds), rendering the German Physics Olympiad reasonably representative in this regard. The survey also revealed that entry rounds of national Physics Olympiads are typically decentralised, while the higher rounds become more and more centralised, similar to the German Physics Olympiad. Another similarity across these Olympiads is the notable increase in the proportion of experimental problems towards the higher rounds, similar to the German Physics Olympiad's approach. A huge difference between countries relates to the number of participants in the entry rounds, ranging from few to half a million students. While these differences may be partly attributed to the different populations, other factors come into play, including pre-selection procedures, voluntary vs. mandatory participation, specialised preparatory trainings for students, and culturally different values assigned to such Olympiads. Such differences do not only exist on a national level, but also regionally, and even between schools in the same city. Consequently, establishing a definitive prototype for a Physics Olympiad proves challenging. Nonetheless, we argue that the German Physics Olympiad can be regarded prototypical among other Physics Olympiads globally, employing criteria based on their shared characteristics, such as the number of selection rounds, the transition from decentralised to centralised rounds, and the increasing emphasis on experimental problems in higher competition rounds. Furthermore, we argue that the German Physics Olympiad can also serve as a prototype for Olympiads centred on other science domains or even science in general. While each science domain has its unique focus and methods, they all share fundamental principles (common scientific methodology and practices, overlapping concepts). These core principles should remain central in science Olympiads across domains, attracting similar groups of students irrespective of the specific science domain.

Theoretical framework and relevant constructs

For this study, the expectancy-value model of achievement-related choices (e.g. Eccles, 2011) was chosen as theoretical framework as it incorporates various person characteristics and their relationship with achievement-related choices (such as science career aspirations) and performance (for example in science Olympiads). The expectancy-value model has previously been applied in science Olympiad settings to understand participants' career aspirations (Garrecht et al., 2023; Steegh et al., 2021a) and to explain exceptional performance in the competition (Stang et al., 2014; Steegh et al., 2021b; Urhahne et al., 2012). Given that the Physics Olympiad targets students passionate about physics who possibly wish to showcase their abilities and invest effort in honing them, we selected the matching expectancy-value constructs physics interest, physics self-efficacy, and grit as profile defining constructs. Moreover, as science Olympiads typically revolve around participants' abilities to solve demanding theoretical (and experimental) science problems, we decided to also select cognitive person characteristics from the expectancy-value model. Thus, in addition to the aforementioned affective constructs (physics interest, physics self-efficacy, and grit), we decided to use participants' general cognitive abilities and domain-specific cognitive abilities (physics problem solving abilities) for profile definition. While we acknowledge that both physics interest and physics self-efficacy encompass a cognitive component alongside their affective component (e.g. Bandura, 1997; Renninger & Hidi, 2011), we refer to them as affective characteristics to differentiate them from solely cognitive characteristics. In summary, we intend to utilise physics interest, physics self-efficacy, and grit as affective characteristics and general and domain-specific cognitive abilities as cognitive characteristics to establish a differentiated characterisation of Physics Olympiad participants.

Literature review on characteristics of science Olympiad participants

Science Olympiad participants are typically assumed to have highly developed cognitive abilities. Participants' domain-specific cognitive abilities were typically operationalised by their grades in science domains and generally found excellent, even beyond science domains (e.g. Campbell, 1996). Balta and Asikainen (2019) found Physics Olympiad participants to have far better developed problem solving abilities than non-participating students. Lind and Friege (2001) found that participants of the Physics Olympiad and non-participating students with comparable age and level of education did not differ in terms of their general cognitive abilities. When solely focussing on science Olympiad participants, however, findings regarding general cognitive abilities are more inconsistent. On one hand, Urhahne et al. (2012) compared more and less successful participants in the Chemistry Olympiad based on their nonverbal cognitive abilities (figurative thinking) and found a significant difference with medium effect size. On the other hand, Stang et al. (2014) conducted an almost identical study within the Biology and Chemistry Olympiad and found no significant difference in participants' nonverbal general cognitive abilities.

Students participating in science Olympiads are also typically described as having favourable affective characteristics as prerequisites for engaging in a science career. They have been confirmed to be highly interested in science domains (Campbell, 1996; Forrester, 2010). Participants' self-efficacy was also found generally high (Steegh et al., 2021a). Moreover, participants are said to show high willingness to exert effort (Urhahne et al., 2012) which relates to a person's level of grit. Grit can be described as an individual's perseverance of effort and passion for certain long-term goals (Duckworth et al., 2007). However, there exists evidence that the group of science Olympiad participants is rather heterogeneous regarding their affective characteristics. Campbell and Feng (2010) found that more and less successful participants differed in their levels of motivation. Steegh et al. (2021a) was able to identify notable differences in Chemistry Olympiad participants' interests which is in accordance to findings of Lind and Friege (2004) who identified subgroups of Physics Olympiad participants with varying levels of physics interest. In total, science competition participants seem to show considerable variance regarding their affective characteristics instead of being a homogeneous group.

An in-detail characterisation of science Olympiad participants becomes increasingly complicated if both cognitive as well as affective student characteristics are considered. For example, one can expect to find highly skilled participants with different levels of motivation and highly motivated participants with different levels of abilities. The relationship between such specific patterns in participants' cognitive and affective characteristics and participants' science competence and career aspirations cannot be broken down to individual effects of specific characteristics on, for example, career aspirations due to the characteristics' high interrelatedness (e.g. Seidel, 2007). Moreover, there are additional factors that seem to influence participant characteristics as well as science competence and career aspirations. More competent participants were found to be – on average – more often of the male gender, older, and had received more parental support than their peers (e.g. Steegh et al., 2021a). In other studies, participants reported they perceived parental support and a home atmosphere conducive to learning as important for the development of science competence (e.g. Campbell, 1996; Nokelainen et al., 2004). Moreover, science Olympiad participants reported support by specific teachers as an important factor in their development of competence and interest (Lind & Friege, 2001). Female gender was also found to be related to lower motivation of science Olympiad participants (Steegh et al., 2021a). Moreover, previous participation in a science competition was found to be associated with higher science interest and stronger self-efficacy beliefs (Höffler et al., 2019).

Altogether, existing studies primarily point out relations between separate variables. However, since these variables were generally shown to interact, it remains unclear what conclusions to draw for individual participants. Thus, there exists a rather diffuse and incomplete picture of the interplay of science Olympiad participants' cognitive and affective characteristics, their relation to science competence and career aspiration, and the role of factors such as age, gender, and social support.

A holistic approach

Holistic approaches seek to understand a subject or problem in its entirety, trying to consider all relevant factors and in particular their interactions at the same time, rather than focussing on isolated aspects, to provide a more comprehensive and nuanced understanding. They are seen as valuable when dealing with complex, multifaceted problems since breaking them into smaller parts for analyses might miss the big picture and lead to wrong conclusions (Teig et al., 2020). Thus, holistic approaches seem particularly suited for establishing a differentiated characterisation of science competition participants that recognises the complexity and interplay of student characteristics. One form of holistic approaches are person-centred approaches that describe similarities and differences among individuals in terms of how relevant characteristics of individuals interplay while assuming that the population under investigation is heterogeneous with respects to the interactions between the characteristics (Laursen & Hoff, 2006). In practise, these approaches search for unobserved or latent subgroups of individuals (so-called profiles) within the population under investigation, whereby these subgroups are described by similar patterns of characteristics within subgroups and different patterns between subgroups.

Using such a person-centred approach, Steegh et al. (2021a) identified four Chemistry Olympiad participant profiles (fearful pessimists, worried optimists, average participants, and carefree participants) based on affective characteristics such as self-efficacy and interest. Their results suggest three distinct levels of motivation among participants, i.e., highly, averagely, and least motivated participants. However, it remains unclear how those motivational levels intertwine with participants' cognitive characteristic. Specifically, findings by Seidel (2007) suggest such an interplay between cognitive and affective student characteristics. Seidel (2007) also used a holistic approach. She investigated regular secondary school students in physics classes and identified five profiles (strong, uninterested, underestimating, overestimating, and struggling) characterised by specific patterns in students' cognitive (physics content knowledge, general cognitive abilities) and affective characteristics (physics interest, physics self-concept of ability). We hypothesise the existence of similar profiles among Physics Olympiad participants (but in different proportions) as they can be regarded a subgroup of the population in Seidel's study.

The present study

To establish a differentiated picture of science Olympiad participant characteristics, this study aimed to identify participant profiles based on participants' cognitive and affective characteristics using a person-centred approach. For this purpose, we chose to focus on participants of the German Physics Olympiad – a prototypical science Olympiad. Moreover, we chose physics problem solving abilities and general cognitive abilities as cognitive and physics interest, physics self-efficacy, and grit as affective participant characteristics. Additionally, we aimed to understand how participants' physics competence and physics career aspirations differ across profiles. We furthermore argue that profile membership is not fixed and transitions can occur as both cognitive and affective characteristics are malleable and can change over time (e.g. Ericsson et al., 1993; Kubsch et al., 2022). While our data's cross-sectional nature prevents us from directly uncovering participants' transitions between profiles, we can still make data-driven recommendations to promote favourable transitions between profiles through support activities by knowing about participant profiles and their relation to competence and career aspirations. This naturally raises the question of the extent to which covariates such as grade level, gender, previous participation, teacher support, and parental support may facilitate or hinder favourable transitions of participants between profiles. This question can at least be answered indirectly using cross-sectional data by examining how specific covariates predict profile membership. In summary, this study aimed to answer the following research questions:

RQ1: Which profiles of Physics Olympiad participants can be identified using cognitive (physics problem solving ability, general cognitive abilities) and affective characteristics (physics interest, physics self-efficacy, grit) as profile indicators?

RQ2: How does profile membership relate to participants' physics competence and physics career aspirations?

RQ3: To what extent can profile membership be predicted by grade level, gender, previous participation in the Physics Olympiad, and perceived support by teachers and parents?

Methods

This study was situated within a larger research project investigating the development of successful and unsuccessful participants in major science competitions in Germany including the Physics Olympiad. All students who registered for one of the competitions under investigation received an invitation to voluntarily participate in the project which consisted of multiple online surveys accompanying the competition. In this particular study, we used data from the first two surveys employed in the Physics Olympiad. Students could complete the first survey starting with the online provision of the first-round problems until receiving a notification about their results in the first round. This first survey covered participants' physics interest, physics self-efficacy, grit, their physics career aspirations, as well as information about their grade level, gender, previous participation, teacher support, and parental support. All students who completed the first survey were invited to the second survey at the start of the second competition round, regardless of their success in first competition round. This second survey covered instruments measuring participants' general cognitive abilities and their physics problem solving abilities. Again, students had time to complete the survey until receiving a notification of their second-round results. Instruments measuring cognitive characteristics were not part of the first survey to prevent excessive burden on participants.

Participants

In the year of data collection, a total of 931 students decided to participate in the Physics Olympiad (28% identified as female; age: $M = 16.3$ years, $SD = 1.1$ years). Of those 931 students, a total of 155 students participated in this study and completed an online survey (32% identified as female; age: $M = 16.3$ years, $SD = 1.1$ years). The majority of students in this sample (97%) attended academic track (*Gymnasium*). The average highest round reached in the Physics Olympiad (which consists of four rounds in total) was 1.51 ($SD = 0.65$), compared to 1.65 ($SD = 0.70$) for the subgroup of participants in this study. This suggests that our sample can be considered representative of all Physics Olympiad participants in terms of age, gender ratio, and average performance in the competition.

Instruments

Cognitive characteristics involved participants' general and domain-specific cognitive abilities. General cognitive abilities were assessed using the subscale for quantitative abilities of the cognitive abilities test by Heller and Perleth (2007) in which students receive different items according to their grade level. For obtaining comparable general cognitive ability scores across participants, even though they received different items, we performed a Rasch analysis (WLE reliability = .77; see Supplemental Materials for further information). To assess physics problem solving ability as a domain-specific cognitive ability, we used an instrument that focusses on students' problem solving strategies and requires students to describe in full sentences how they would solve four well-defined physics problems without explicitly solving them (for a full description of the instrument, see Wulff et al., 2023). Students' responses in this problem solving test were entirely double coded by two independent raters. Initial agreement between the raters measured through Cohen's linearly weighted kappa (Warrens, 2012) was almost perfect ($\kappa = .81$; Landis & Koch, 1977). To further increase the quality of ratings, disagreements between the raters were discussed until a consensus was reached.

Affective characteristics included physics interest, physics self-efficacy, and grit which were measured with instruments using four-point Likert scales ranging from 'I completely disagree' (1) to 'I completely agree' (4). The number of items in each instrument as well as internal consistencies measured through Cronbach's alpha are given in brackets. Physics interest (four items; $\alpha = .82$) was measured with the physics topic interest measure developed by Daniels (2008). Physics self-efficacy (four items; $\alpha = .87$) was measured with an adapted version of the mathematics self-efficacy scale from PISA-Konsortium Deutschland (2006). Participants' grit (eight items; $\alpha = .70$) was measured with a selection of items from the grit scale by Duckworth et al. (2007).

Science competence is regarded as the underlying cause of performance in science (e.g. Chomsky, 1965) which is why we used students' performance in the Physics Olympiad operationalised by their highest reached competition round (ranging from one to four) as an indicator for physics competence. *Physics career aspiration* (three items; $\alpha = .93$) was measured using an adapted version of the scale for long-term goals by Urhahne et al. (2012).

Lastly, this study aimed at examining the roles of selected covariates for predicting profile membership. Participants' *grade level*, *gender*, and *previous participation* (i.e. whether a student had already participated in the Physics Olympiad at least once) were directly assessed in the survey. For measuring participants' perceived *teacher support* (three items; $\alpha = .78$) and *parental support* (six items; $\alpha = .82$) we used an instrument developed by Wulff et al. (2018).

An overview of almost all utilised items of the described instruments can be found in the Supplemental Materials.

Statistical analyses

The main analyses were conducted using Mplus Version 8.7 (Muthén & Muthén, 1998–2017). All aspects regarding data pre-processing and measurement invariance testing are described in the Supplemental Materials.

To answer RQ1, i.e. to identify profiles of Physics Olympiad participants based on cognitive and affective characteristics (lower part of Figure 1), we used latent profile analysis (LPA) as a person-centred approach. LPA aims at identifying latent subpopulations (profiles) within the population under investigation based on a predefined set of indicator variables (Spurk et al., 2020). Before performing the LPA, all non-categorical variables were standardised ($M = 0$, $SD = 1$) to facilitate future interpretation of profiles relative to each other. We then performed a series of LPA with varying model specifications and with up to six profiles. We used robust maximum likelihood estimation to address potential non-normality of data. To address the potential issue of local maxima in each analysis, we performed 40.000 random starts with 100 iterations per random start. Additionally, the best 10.000 solutions identified by the highest likelihood values went through final-stage optimisation (Hipp & Bauer, 2006). To identify the optimal solution, we compared all solutions of the different models (i.e. different model specifications and varying numbers of profiles) based on various fit statistics,

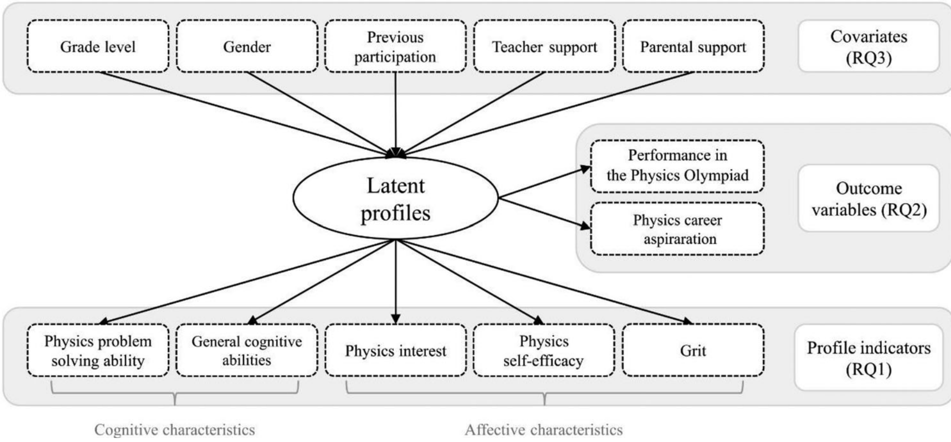

Figure 1. Analysis framework including profile indicators (RQ1), outcome variables (RQ2), and covariates (RQ3).

profile sizes, and substantive interpretability of resulting profiles. Fit statistics involved the Akaike information criterion (AIC), the Bayesian information criterion (BIC), and the sample-size adjusted BIC (SABIC), whereby lower values of each criterion indicate parsimony and better fit (Weller et al., 2020). Moreover, we used entropy as a measure which indicates the ability of the model to provide well-separated profiles (Celeux & Soromenho, 1996). Entropy values range from 0 to 1 with higher values representing better classification accuracy, while values greater than 0.8 are seen to indicate adequate classification accuracy (Clark & Muthén, 2009). We also performed Lo-Mendell-Rubin adjusted likelihood ratio tests (LMR-LRT; Lo et al., 2001) and bootstrapped likelihood ratio tests (BLRT; McLachlan et al., 2019), whereby a significant *p*-value indicates that the current model fits better than the same model with one less profile.

To answer RQ2, i.e. to examine the relationships between profile membership and performance in the Physics Olympiad (as an indicator for physics competence) as well as physics career aspirations (middle part of Figure 1), we used the BCH function implemented in Mplus which computes profile-specific means and tests their equality using Wald chi-square tests.

To answer RQ3, i.e. to predict profile membership using grade level, gender, previous participation, teacher support, and parental support as covariates, we used Mplus' R3STEP function which performs a multinomial logistic regression. More precisely, all profiles are compared pairwise in terms of membership probabilities based on the introduced covariates (top part of Figure 1). Since resulting regression coefficients are hard to interpret, better interpretable odds ratios (*OR*) were also computed. Further information regarding the BCH and R3STEP function can be found in the Supplemental Materials.

Results

Descriptive statistics

Table 1 shows the descriptive statistics of all (unstandardised) variables and particularly illustrates that physics interest, physics self-efficacy, and career aspirations of Physics

Table 1. Descriptive statistics of profile indicators, outcome variables, and covariates.

	Scale	*M*	*SD*	min	max	Skewness
Profile indicators:						
Physics problem solving ability	−8, … , 32	7.46	6.75	−2	30	0.77
General cognitive abilities	Rasch	0.55	0.95	−1.96	3.08	−0.48
Physics interest	1–4[a]	3.38	0.59	1.75	4	−0.82
Physics self-efficacy	1–4[a]	3.29	0.61	1.25	4	−0.93
Grit	1–4[a]	2.86	0.44	1.75	4	−0.23
Outcome variables:						
Performance in the Physics Olympiad	1, 2, 3, 4	1.65	0.70			
Physics career aspiration	1–4[a]	3.16	0.84	1	4	−0.81
Covariates:						
Grade level	7, … , 13	11.15	1.00	8	13	−0.85
Gender	0, 1[b]	0.32				
Previous participation	0, 1[c]	0.60				
Teacher support	1–4[a]	3.15	0.69	1	4	−0.75
Parental support	1–4[a]	2.46	0.70	1	4	0.15

Notes: *M* = scale mean, *SD* = standard deviation, min/max = minimum/maximum value that actually occurred.
[a]These scales were created by averaging the responses to the corresponding four-point Likert items.
[b]Female gender corresponds to 1.
[c]Having previously participated corresponds to 1.

Olympiad participants were generally high but still exhibited notable variance. Correlations between all variables are found in Table S2 in the Supplemental Materials and suggest a complex interplay between variables due to several significant correlations.

Identification of participant profiles (RQ1)

We used latent profile analysis (LPA) to identify participant profiles which involves deciding on the most optimal solution among different model specifications and varying numbers of profiles. Model fit statistics indicated that a model specification with freely varying variances and zero covariances provided the best fitting solutions among the considered model specifications (see Figure S1 in the Supplemental Materials). Model fit statistics for this model specification with up to six profiles are shown in Table 2. BIC values were the lowest for the three- and four-profile solutions, indicating that these solutions best fit the data. Both the LMR-LRT and the BLRT suggested that the four-profile solution does not fit significantly better (i.e. $p > .05$) than the three-profile solution. Since both these solutions had a similar satisfying entropy value (indicating adequate classification accuracy), we decided to examine further classification diagnostics (see Table S3 in the Supplemental Materials) which

Table 2. Model fit statistics for latent profile solutions with up to six profiles.

#	LL	AIC	BIC	SABIC	Entropy	LMR-LRT	BLRT	Profile sizes
1	−1097.2	2214.3	2244.8	2213.1				155
2	−1037.7	2117.4	2181.3	2114.8	.73	.013	.000	86, 69
3	−998.1	2060.2	2157.6	2056.3	.82	.006	.000	58, 50, 47
4	−971.3	2028.6	2159.5	2023.4	.82	.123	.333	55, 41, 41, 18
5	−954.0	2016.0	2180.4	2009.4	.86	.342	1.	53, 40, 33, 19, 10
6	−936.9	2003.7	2201.5	1995.8	.90	.369	1.	58, 39, 28, 17, 8, 5

Notes: # = number of profiles, LL = log-likelihood, AIC = Akaike information criterion, BIC = Bayesian information criterion, SABIC = sample-size adjusted BIC, LMR-LRT = *p*-value of the Lo-Mendell-Rubin adjusted likelihood-ratio test, BLRT = *p*-value of the bootstrapped likelihood-ratio test. These fit statistics correspond to a model specification with freely varying variances and zero covariances.

provided a small argument for selecting the four-profile solution over the three-profile solution.

As there was no compelling empirical argument in favour of selecting one profile solution over the other, we decided to conduct a more substantive examination of the three- and four-profile solutions. To do this, we visualised both solutions to compare the identified profiles between the two (see Figure S2 in the Supplemental Materials). The first thing to note is that two profiles in the three-profile solution have an almost perfect structural similarity to two profiles in the four-profile solution. This particularly means that the remaining profile in the three-profile solution is split up into two separate profiles in the four-profile solution. For both solutions, we then tried to construct a mapping between our identified profiles and the profiles of secondary school students in physics classes established by Seidel (2007). This way, we found that the four-profile solution was clearly more in congruence with the profiles identified by Seidel (2007), in comparison to the three-profile solution (see the note of Figure S2 in the Supplemental Materials). Thus, the four-profile solution was selected as the most optimal and considered for further investigations.

The four-profile solution is presented in Figure 2. The vertical axis represents z-scores, i.e. standard deviations above or below the sample mean, as all profile indicators were standardised before conducting the LPA because corresponding instruments had not the same scales (see Table 1). Therefore, profile-specific means of profile indicators must always be interpreted relatively to the average characteristics of the entire study sample (see also Table 1). By examining Figure 2, one recognises that all profile indicators except for grit contributed to the appearance of substantively different profiles. All estimated profile-specific means and variances (including standard errors) of this solution are provided in Table S4 in the Supplemental Materials.

Profiles were labelled based on their relative affective characteristics (*highly*, *averagely*, and *least motivated*) and on terminology of expertise research (*experts* vs. *novices*).

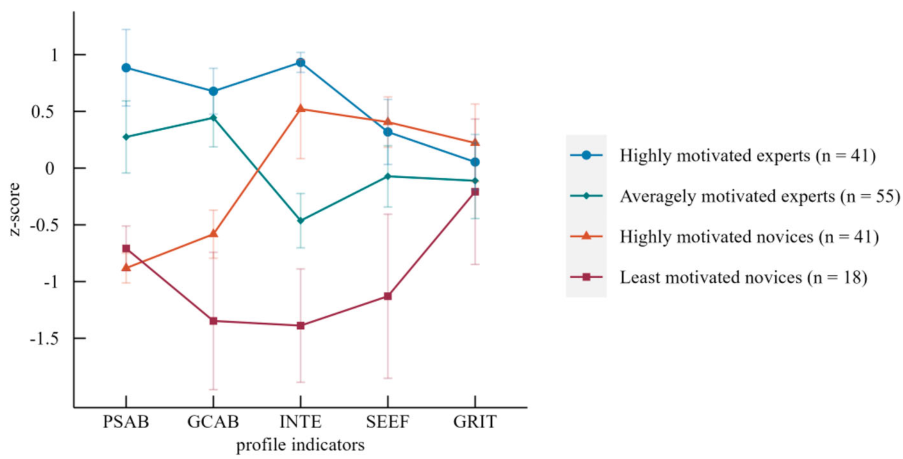

Figure 2. Four-profile solution with profile-specific means of profile indicators on standardised scales and corresponding 95% confidence intervals.

Note. PSAB = physics problem solving ability, GCAB = general cognitive abilities, INTE = physics interest, SEEF = physics self-efficacy, GRIT = grit.

Participants in the *highly motivated expert* profile ($n = 41$; 26.5%) show the highest cognitive abilities and the strongest interest in physics compared to the other profiles. Moreover, they are characterised by above-average physics self-efficacy. Participants in the *averagely motivated expert* profile ($n = 55$; 35.4%) show a similar pattern although slightly lower on all profile indicators compared to the *highly motivated expert* profile, with the exception of physics interest which is clearly below-average. While participants in the *highly motivated novice* profile ($n = 41$; 26.5%) are characterised by below-average cognitive abilities, they clearly show strong physics interest and physics self-efficacy. Finally, the *least motivated novice* profile ($n = 18$; 11.6%) is by far the smallest profile whereby all indicator variable means (except for grit) are slightly or severely below-average.

Profile-specific physics competence and career aspirations (RQ2)

We wanted to understand how profile membership relates to participants' physics competence (indicated by performance in the Physics Olympiad) and physics career aspirations. Results on these relationships in the form of profile-specific means and pairwise equality tests are presented in Table 3. We found significant differences across profiles regarding performance operationalised by students' highest reached round in the Olympiad ($\chi^2_{\text{overall}} = 33.95$, $p \leq .001$). There were no significant differences between the two *expert* profiles nor between the two *novice* profiles, however, all pairwise equality tests between an *expert* profile and a *novice* profile revealed significant differences. Overall, the *highly motivated expert* profile ($M = 2.07$) and the *averagely motivated expert* profile ($M = 1.74$) performed best while the *highly motivated novice* profile ($M = 1.24$) and the *least motivated novice profile* ($M = 1.38$) performed worst.

Students' physics career aspirations also differed significantly across profiles ($\chi^2_{\text{overall}} = 63.64$, $p \leq .001$). Specifically, all pairwise equality tests between profiles revealed significant differences except for the comparison of the *highly motivated expert* profile and the *highly motivated novice* profile. In total, we obtained the following ranking: The *highly motivated expert* profile ($M = 0.68$) and the *highly motivated novice* profile ($M = 0.40$) both displayed the highest physics career aspirations, followed by the *averagely motivated expert* profile ($M = -0.30$) and the *least motivated novice* profile ($M = -1.16$).

Table 3. Relationship between profile membership and participants' performance in the Physics Olympiad and their physics career aspirations.

			Wald χ^2-test		
	M	*SD*	1.	2.	3.
Performance in the Physics Olympiad:					
1. Highly motivated experts	2.07	0.13			
2. Averagely motivated experts	1.74	0.10	3.64		
3. Highly motivated novices	1.24	0.08	28.07***	13.13***	
4. Least motivated novices	1.38	0.12	15.22***	4.75*	0.88
Physics career aspiration:					
1. Highly motivated experts	0.68	0.10			
2. Averagely motivated experts	−0.30	0.14	29.28***		
3. Highly motivated novices	0.40	0.14	2.29	11.52***	
4. Least motivated novices	−1.16	0.26	41.99***	7.67**	25.88***

Notes: M = profile-specific means, SD = standard deviation; *$p \leq .05$, **$p \leq .01$, ***$p \leq .001$.

Table 4. Results of the multinomial logistic regression for the effects of covariates on profile membership.

	Highly motivated experts			Averagely motivated experts			Highly motivated novices		
	β	*SE*	*OR*	*β*	*SE*	*OR*	*β*	*SE*	*OR*
Reference profile: Averagely motivated experts									
Grade level	−0.07	0.29	0.93						
Gender	−0.10	0.54	0.90						
Previous participation	0.35	0.52	1.42						
Teacher support	−0.08	0.26	0.93						
Parental support	−0.17	0.31	0.85						
Reference profile: Highly motivated novices									
Grade level	0.58*	0.30	1.78	0.65*	0.30	1.91			
Gender	−0.42	0.60	0.65	−0.32	0.55	0.73			
Previous participation	1.39**	0.56	4.01	1.04*	0.54	2.83			
Teacher support	−0.10	0.29	0.91	−0.02	0.31	0.98			
Parental support	−0.30	0.31	0.74	−0.13	0.26	0.88			
Reference profile: Least motivated novices									
Grade level	0.22	0.43	1.24	0.29	0.44	1.34	−0.36	0.39	0.70
Gender	−1.15	0.76	0.32	−1.04	0.75	0.35	−0.72	0.73	0.49
Previous participation	0.84	0.68	2.31	0.49	0.68	1.63	−0.55	0.67	0.58
Teacher support	0.70	0.40	2.02	0.78	0.42	2.18	0.80*	0.38	2.23
Parental support	−0.71	0.42	0.49	−0.54	0.43	0.58	−0.41	0.39	0.66

Notes: β = regression coefficient, *SE* = standard error, *OR* = odds ratio; significance of regression coefficients: $^{*}p \leq .05$, $^{**}p \leq .01$, $^{***}p \leq .001$.

Prediction of profile membership (RQ3)

To examine how selected covariates predict profile membership in order to determine possible factors facilitating or hindering favourable transitions of participants between profiles, we used a multinomial logistic regression, the results of which are shown in Table 4. Students in higher grade levels were found significantly more likely to be in the *highly motivated expert* profile or in the *averagely motivated expert* profile than in the *highly motivated novice* profile (*OR* = 1.78/1.91, resp.). Similarly, students that had at least participated once in the Physics Olympiad were significantly more likely to be in the *highly motivated expert* profile or in the *averagely motivated expert* profile than in the *highly motivated novice* profile (*OR* = 4.01/2.83, resp.). Moreover, we found that students who reported higher teacher support were significantly more likely to be in the *highly motivated novice* profile than in the *least motivated novice* profile (*OR* = 2.23). Lastly, even though not significant, respective odds ratios suggest female students to be less likely in the *highly motivated expert* profile or in the *averagely motivated expert* profile than in the *least motivated novice* profile (*OR* = 0.32/0.35, resp.) and less likely to be in the *highly motivated novice* profile than in the *least motivated novice* profile (*OR* = 0.49).

Discussion

The purpose of this study was to develop a diverse, differentiated, and holistic picture of the participants of the German Physics Olympiad as a prototypical science Olympiad. We employed latent profile analysis as a person-centred approach to capture the interrelatedness of cognitive and affective characteristics of participants. We identified participant profiles, examined the relationship between profile membership and students' performance and career aspirations, and determined factors facilitating or hindering favourable transitions between profiles by predicting profile membership through several covariates. In the following, we will discuss our results and their implications for more individualised and targeted support activities within the Physics Olympiad in particular and within Olympiad-type competitions in more general.

Identification of participant profiles (RQ1)

Our analyses revealed four participant profiles: (i) *highly motivated experts*, (ii) *averagely motivated experts*, (iii) *highly motivated novices*, and (iv) *least motivated novices*.

Students in the *highly motivated expert* profile have excellent prerequisites for a physics career as they are characterised by comparably positive cognitive and affective characteristics. They particularly excel in problem solving which is considered an essential activity in science professions (Armour-Garb, 2017; Mulvey & Pold, 2020).

The *averagely motivated expert* profile is comparable to the *highly motivated expert* profile, but students in the former are less interested in physics. This difference could be attributed to the phenomenon of multipotentiality. Talented individuals often exhibit multipotentiality, i.e. they possess considerably proficiency and interest in multiple domains (Rysiew et al., 1999). Specifically, more successful Physics Olympiad participants were often found to be interested in multiple domains beyond physics (Lind & Friege, 2001). The *averagely motivated expert* profile might therefore consist mainly of multipotential students who – due to their scattered interests – may not have developed an extraordinary high interest in physics compared to students in the *highly motivated expert* profile.

Students in the *highly motivated novice* profile are characterised by comparably lower cognitive abilities, strong physics interest, and high levels of physics self-efficacy. Student profiles with conflicting information (i.e. some characteristics are highly developed while others are less developed) such as this one are generally at risk of being perceived by educators as more homogeneous regarding their characteristics than they actually are (Südkamp et al., 2018). This issue might be particularly present in science Olympiads: Given that participants are generally assumed to be more motivated to engage in science compared to their peers, competition organisers and instructors are at risk of overestimating those students' cognitive abilities even though no relevant information is available (Halo effect; see e.g. Nisbett & Wilson, 1977). Moreover, the combination of high self-efficacy and comparably lower cognitive abilities puts these students at risk of overestimating their abilities compared to other participants' abilities. The big-fish-little-pond effect (Marsh et al., 1995) may explain this disadvantageous combination of characteristics: Students may belong to the top group in their physics classes and hence have highly developed self-efficacy beliefs. However, when participating in the Physics Olympiad or another science competition for the first time, these students' abilities might be comparatively below average. These students' self-efficacy beliefs, however, remain on a high level, resulting in an overestimation of individual abilities within the competition. Failure in the competition might then have negative impacts such as a decrease in the originally strong self-efficacy or interest. This hypothetical effect represents an important issue within science competitions and should be addressed within future research.

The *least motivated novice* profile consisted of relatively few students with both below-average cognitive and affective characteristics. However, taking into account that Physics Olympiad participants were on average strongly interested in physics and had on average strong physics self-efficacy beliefs (see Table 1), it becomes clear that even the *least motivated novice* profile is actually averagely motivated in absolute terms (see unscaled means in Table S4). This also better fits into the overall picture as one would not expect unmotivated students to voluntarily participate in an out-of-school science activity.

We also examined grit as a profile indicator, however, it did not contribute to any notable differences between profiles. An empirical reason for this might be the overall low variance of grit in our sample (see Table 1). If there were profiles characterised by clearly separable levels of grit, we would expect to observe notable variability in grit scores within the total sample. This low variance of grit (in combination with its above-average value) can be ascribed to the fact that our sample represents a self-selected group from more privileged socio-economic backgrounds (Gorski, 2016; Kwon, 2018). The majority of Physics Olympiad participants attended academic track (97%) which can be considered an indicator for better socio-economic conditions (Dumont et al., 2014). Overall, we argue that one possible explanation for grit playing no role in explaining profile differences is that all students regardless of profile membership exhibit similar levels of grit due to their collectively more privileged socio-economic backgrounds.

Overall, the four identified profiles align with the generally accepted understanding that motivation (which includes interest and relates to self-efficacy) notably influences the amount of time that people are willing to invest in their learning, i.e. in their expertise development (Bransford et al., 2000). Both *expert* profiles exhibited at least well-developed interest and self-efficacy beliefs in absolute (unscaled) terms (see Table S4 in the Supplemental Materials). In contrast, the two *novice* profiles differed greatly with regards to their levels of interest and self-efficacy beliefs. Thus, our profile structure underscores that motivational aspects (i.e. interest and self-efficacy) represent a necessary but not sufficient condition for the development of expertise.

Profile-specific physics competence and career aspirations (RQ2)

We used performance in the Physics Olympiad, operationalised by participants' highest reached competition round, as an indicator for physics competence. First, we can conclude that participants' level of expertise seems to be decisive for performance in the Physics Olympiad, as both *expert* profiles (characterised by higher cognitive abilities) outperformed both *novice* profiles (characterised by lower cognitive abilities). Second, we can conclude that a lack of cognitive abilities cannot be compensated for by high levels of interest or self-efficacy when it comes to performance in the Physics Olympiad. This becomes apparent when comparing the two *novice* profiles, both of which exhibited below-average cognitive abilities. Even though the *highly motivated novice* profile demonstrated notably greater physics interest and self-efficacy than the *least motivated novice* profile, there was no significant difference in their performance. Thus, it seems that physics interest and self-efficacy do not directly influence performance in the Physics Olympiad. Moreover, when participants have already attained a high level of expertise in physics, which goes alongside substantial physics interest, further increases in interest do not relate with improved performance. This becomes evident when comparing the performances of both *expert* profiles, which primarily differ in their physics interest, but not in their performance in the Physics Olympiad. In summary, we argue that participants' cognitive characteristics predominantly influence their performance in the Physics Olympiad. Moreover, although the affective characteristics physics interest and physics self-efficacy may not have a direct impact on performance, they serve as prerequisites for the development of expertise among novices and are thus crucial for future performance.

Findings with regard to profile-specific physics career aspiration indicate that the examined affective characteristics (except for grit) are of high importance while cognitive characteristics seem to play a negligible role. This is in line with previous research that found both interest and self-efficacy positively related to career aspiration (e.g. Nugent et al., 2015). However, self-efficacy beliefs relate to cognitive characteristics as they represent individuals' beliefs about their own abilities. For example, a student belonging to the *highly motivated novice* profile will typically be characterised by relatively low cognitive abilities, strong physics interest, high self-efficacy, and also a high physics career aspiration. Engaging in a physics career, this student may be at disadvantage due to possible overestimation of one's own abilities compared to what is expected when studying physics. Hence, the Physics Olympiad should aim to assist these participants in gaining valuable insights into their current strengths and weaknesses. In particular, this would benefit students belonging to the *highly motivated novice* profile who contemplate engaging in a science career, as it would make them aware of the need to develop their (domain-specific) cognitive abilities. Ideally, the Physics Olympiad should include support activities that focus on developing such abilities.

Prediction of profile membership (RQ3)

We examined how selected covariates predict profile membership in order to determine possible factors facilitating or hindering favourable transitions of participants between profiles. Students in higher grade levels or students who participated in the Physics Olympiad before were significantly more likely found to be in one of the *expert* profiles than in the *highly motivated novice* profile, which coincides with the fact that expertise develops over time (e.g. Ericsson et al., 1993). Specifically, participation in science Olympiads seems to offer beneficial opportunities for deliberate practise which potentially leads to the development of expertise.

Among students in the *novice* profiles, those who reported greater perceived support from their teachers were more likely to be classified in the *highly motivated novice* profile than in the *least motivated novice* profile. This finding is in accordance with prior literature that highlights the crucial role of teachers, and educators in general, in arousing and reinforcing students' motivation within a specific domain (e.g. Wentzel et al., 2010). Teachers typically encourage students to participate in science competitions (Abernathy & Vineyard, 2001). As a result, they often serve as the initial resource students turn to when seeking support. Accordingly, teachers play a crucial role in students' development of science competence and career aspirations. Overall, we argue that teachers should be aware of the role they play in motivating novice students, not only within the realm of science competitions but in the broader context of general education.

The finding that female participants were more likely to be classified in the *least motivated novice* profile than in any other profile highlights existing gender differences in science competitions (see Steegh et al., 2019). However, a study by Ladewig et al. (2022) suggests that the German Physics Olympiad is equally supportive for female and male participants, i.e. female participants were neither found to be susceptible to stereotype threat nor to social identity threat. In fact, previous research indicates that female students generally have lower science knowledge, lower science self-efficacy, and lower science interest (Leslie et al., 2015; Osborne et al., 2003; Seidel, 2007). This might directly transfer to the competition environment which is why it represents a greater systemic problem that requires further research and actions in the right direction.

Implications for more targeted and individualised support in science competitions

In view of our findings and the goal of science competitions to support participating students in their development of science competence and career aspiration, students should be ideally manoeuvred towards the *highly motivated expert* profile. This manoeuvring of science competition participants towards the *highly motivated expert* profile can be realised through individualised and targeted support activities (within and beyond the competition) based on students' current profile membership.

Efforts should be made that students currently in the *highly motivated expert* profile should remain in this profile, particularly as Kubsch et al. (2022) found their most motivated profile to be the most unstable. Overall, more research is needed on how to keep students in this profile. Nevertheless, we suggest offering support activities which try to further increase these students' already high motivation and to even further develop these students' already high physics-specific abilities. To maintain or to even increase their motivation, one could offer internships at research institutes or within physics-related companies. This hands-on experience would allow students to grapple with meaningful research-oriented physics challenges and practical real-world applications of the subject. Moreover, students could get connected to professionals in the field who can serve as valuable role models or mentors, guiding and inspiring the students (Pleiss & Feldhusen, 1995). To further increase these students' already high physics-specific abilities, it is essential to expose them to more complex scientific concepts or applications. This exposure can occur during internships, providing an immersive learning environment. Another opportunity are dual enrolment programmes where students simultaneously participate in college or university courses while maintaining their regular attendance at school (An & Taylor, 2019).

We hypothesised that the *averagely motivated expert* profile might primarily consist of multipotential students who are proficient and interested in multiple domains, which is often accompanied by difficulties in career decision-making (Greene, 2006; Sajjadi et al., 2001). Therefore, authentic and realistic insights into the profession of a physicist should be offered as support activities for this group of students within competition settings. For example, lab tours, excursions to research institutes, or physics-related internships may offer authentic and realistic insights (Vela et al., 2020). Similarly, the usage of scientific video vignettes may promote their perception of authentic science (Stamer et al., 2019) to at least facilitate career decision-making.

Students in the *highly motivated novice* profile may be manoeuvred towards the *highly motivated expert* profile by fostering their physics problem solving abilities and their general cognitive abilities through additional support activities and materials. As participants in this profile are generally less successful in the competition, they seldom move beyond the first competition round which takes place as home work. To address this, corresponding support activities should be designed with consideration for both online and in-school formats. To increase students' problem solving abilities, online materials involving automatic feedback systems could be provided that focus on the problem solving process (e.g. Selçuk & Çalýskan, 2008) and involved problem-solving strategies (e.g. Larkin & Reif, 1979).

We argue that students in the *least motivated novice* profile benefit the most from support activities that address affective instead of cognitive characteristics as expertise cannot be acquired instantaneously but develops over time (e.g. Ericsson et al., 1993). Consequently, students would benefit more from activities that initially manoeuvre students towards the *highly motivated novice* profile. This includes raising students' physics interest which may positively influence their long-term engagement with physics. This, in turn, may positively influence the development of physics expertise (e.g. Feldon et al., 2019) and can be achieved, for example, through interesting and demanding but feasible competition tasks. As female students were found overly represented in this profile, additional activities that support female students' physics engagement could be offered (e.g. Wulff et al., 2018). This includes, for example, matching tasks' topics to female students' interests (e.g. Häussler & Hoffmann, 2002), actively practicing gender awareness in the competition (e.g. CohenMiller et al., 2020), and involving parents to create support for female participants (e.g. Steegh et al., 2021a). Moreover, students' self-efficacy beliefs could be improved in accordance to a growth mindset (Yeager et al., 2019) by employing elements of a growth mindset intervention (e.g. Esparza et al., 2014). However, these measures to promote students' interest and self-efficacy beliefs should also be incorporated into regular school instruction as teachers play an important role in shaping their students' interests and self-efficacy beliefs (e.g. Wentzel et al., 2010).

Having discussed what more individualised and targeted support for science competition participants can look like, the fundamental question on how to recognise which student belongs to which profile still remains. An easy answer would involve having students assign themselves to available support activities. However, due to biased self-perceptions (e.g. overestimation of abilities), suboptimal self-assignment to support activities may occur. Therefore, we propose using a minimalistic assessment of relevant student characteristics at the start of science competitions which provides guidance to students on which support activities to attend. Our findings suggest this assessment to include a short test (e.g. multiple-choice) assessing central facets of domain-specific cognitive abilities as well as key items assessing students' domain interest and domain-specific self-efficacy.

Limitations and future directions

First, a considerable number of assessed variables in our study are self-reported and therefore susceptible to participants' personal convictions which is why our results may be biased to some extent. Future research should aspire a more objective assessment of relevant variables, e.g. assessing parental and teacher support by asking participants how often they receive support and what kind of support. Specifically, it would be interesting to understand whether students actively sought support on their own or whether parents or teachers directly offered support. Second, our data was generally cross-sectional which strongly limits our ability to make causal inferences. Future research would benefit from longitudinal assessments enabling researchers to explore the directionality of relations between profile membership, covariates, and outcomes. Moreover, such longitudinal assessments would allow for the direct examination of the stability of profiles as well as transitions of students between profiles over time. This would provide valuable insights on whether science competitions can initiate favourable transitions of students between profiles over time. Third, our findings are based on one specific science competition. We consider the German Physics Olympiad as a typical Olympiad-type competition characterised by a task-centred nature. It needs to be confirmed to what extent our results extend to other competition formats, such as project-centred competitions. A similar characterisation of participants in a project-based competition, akin to our study's characterisation, would allow for a comparison of participants, providing valuable insights into which competition type (task-centred versus project-centred) is more suitable for a particular student based on this student's individual characteristics.

Conclusion

Our finding indicate that Physics Olympiad participants, who are typically assumed to be a homogeneous group, seem to be conversely a rather heterogeneous group as shown through the occurrence of four different participant profiles. Participants would therefore clearly benefit from more profile-specific support activities within science competitions. In this regard, the applied person-centred approach proved its potential as its results directly translated to profile-specific needs of participants based on which more individualised and targeted support activities were proposed.

Disclosure statement

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Ethical approval

The data used in this study was collected within the WinnerS project. Participation was voluntary and all ethics requirements for human subjects' research were met as testified by the ethics committee of the IPN under the approval number 2022_13_HO.

Language editing

In the process of refining the manuscript, language editing was conducted with the assistance of ChatGPT, a language model developed by OpenAI. ChatGPT was employed to enhance the clarity, coherence, and style of the text while maintaining the integrity of the original content.

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