Students’ approach to learning: evidence regarding the importance of the interest-to-effort ratio

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ABSTRACT
Existing science evidence sustained that students’ preferences for a learning approach (i.e., deep or surface learning) depend on several contextual variables. In this study, we used the network psychometrics perspective to investigate the interactions between the elements that define students’ learning preferences. We aimed to understand which are the central elements of the students’ behavior patterns used when they decide to adopt one specific learning approach. We used the Revised Two-Factor Study Process Questionnaire to collect responses from a large sample of university students (5357 students, 73% female). The results indicated that the interest-to-effort ratio is central to students’ preference for deep or surface learning. Also, we found that the estimated network is stable across different groups defined by the academic disciplines, students’ gender, and year of study. These results are presented as arguments for using the workload and students’ interest as topics in pedagogical programs dedicated to academics.

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Introduction
In today’s higher education, the sustainability of students’ learning is very often associated with deep learning (Warburton, 2003). A deep learning approach involves students understanding the discipline and engaging in meaningful learning (Asikainen & Gijbels, 2017). The deep learning approach usually involves the use of analytic skills, cross-referencing, imaginative reconstruction, and independent thinking, and fosters lifelong learning (Warburton, 2003). The surface learning approach involves the memorization of the course without understanding its implications or utility (Asikainen & Gijbels, 2017), just to give the impression that maximum learning took place. Therefore, the surface learning approach has short-term benefits, but it is detrimental in the long run. Given its
consequences, the students’ learning approach became a highly debated topic that generated numerous research studies (Fryer & Gijbels, 2017).

Reviewing the research on this topic, Dinsmore (2017) concluded that existing scientific evidence sustained that students’ preferences for a learning approach depend on several contextual variables. Thus, research studies investigated contextual variables such as instructional or assessment strategies (e.g., the type of assessment used in the evaluation), the student traits (e.g., gender, interest or goals) and the educational context (e.g., the academic year, academic domains) (Dinsmore, 2017). For example, Al-Kadri et al. (2012) reported that the use of formative assessment is associated with the students’ deep approach to learning, while the summative assessment is associated with students’ surface approach to learning. Dinsmore (2017) highlighted that students’ goals are particularly important for adopting a specific learning approach. Asikainen and Gijbels (2017) focused on the educational context and reviewed the longitudinal studies that investigated the development of students’ approaches to learning during higher education. While some studies reported that students are developing a deep learning approach during higher education, a similar number of studies did not present a clear relationship between the preference for deep learning approach and student tenure. Dinsmore (2017) reviewed 96 studies from different academic domains (e.g., reading or writing, mathematics, engineering, life science), and concluded that studies from the reading and writing domain were more likely to report mixed findings, as compared with studies from mathematics, engineering or life sciences.

In this study, we argue that the students’ preferences for a particular learning approach can be seen as an emergent phenomenon, and we aim to provide evidence regarding its emergence patterns. Using a network analysis framework, we assume that learning approaches can be understood if we analyze the relations between their components. Unlike the traditional latent factor approach, network analysis assumes that the behaviors describe a phenomenon (i.e., learning approach) together because they mutually influence each other (Fonseca-Pedrero, 2017, p. 208). Therefore, network analysis could identify the behaviors or motivations that are most influential in the emergence of the preference for a particular learning approach.

Preferences for study strategies

The most well-known model of preferences for the study comes from Marton (1975), which defined two approaches to learning: deep and surface (Marton & Säljö, 1976a; Marton & Säljö, 1976b). Researchers developed questionnaires for assessing these learning approaches such as the Revised Two-Factor Study Process Questionnaire (R-SPQ-2F; Biggs et al., 2001), the Approaches and Study Skills Inventory for Students (Tait et al., 1998) or the Learning and Studying Questionnaire (Entwistle et al., 2003).

The R-SPQ-2F (Biggs et al., 2001) is one of the most widely used questionnaires for measuring student learning approaches (Asikainen & Gijbels, 2017). This instrument assesses two learning approaches (i.e., deep and surface), and defines two subscales (i.e., motives and strategies) for each approach. The items of R-SPQ-2F (Biggs et al., 2001) describe Deep Motives (DM), Deep Strategies (DS), Surface Motives (SM), and Surface Strategies (SS). Since 2001, the factor structure of the R-SPQ-2F has been investigated in many countries: Spain (Justicia et al., 2008), Australia and Hong Kong (Leung...
et al., 2008), USA (Immekus & Imbrie, 2010), Japan (Fryer et al., 2012), Belgium (Stes et al., 2013), Malaysia (Goh et al., 2017) and Argentina (Freiberg-Hoffmann & Fernández-Liporace, 2016). Although most of these studies confirmed that the two latent factors (i.e., deep and surface approaches) provided acceptable fit, some studies reported that a four-factor solution was superior (Immekus & Imbrie, 2010; Stes et al., 2013). However, several studies did not find support for the differentiation between motive and strategy sub-components (Fryer et al., 2012; Goh et al., 2017; Justicia et al., 2008).

Studies that used R-SPQ-2F also analyzed the influence of different variables on the changes reported in students’ approaches to learning. Smith and Miller (2005) reported that psychology students scored significantly higher than business students on the deep approach, while business students had higher scores on the surface approach of learning. The same authors highlighted that gender had a significant effect on students’ learning approach. Female students could be more likely to adopt strategies associated with the deep approach of learning (Smith & Miller, 2005). A large body of research conducted by using R-SPQ-2F presented evidence that students’ preferences for a learning approach changed over the academic years (e.g., Geitz et al., 2016; Phan, 2013). Given the results of previous studies, we investigated the stability of our network on subsamples based on students’ gender, their academic discipline, and academic year.

**The network psychometrics approach**

The traditional psychometric approach focuses on the estimation of the shared variance between the items that describe a particular behavioral pattern. Traditionally, researchers used latent variables to capture this shared variance and attempted to predict these variables using various theory-driven predictors (e.g., other student characteristics, teacher characteristics). These latent variables are assumed to be the cause of the observed covariances between particular behaviors. In the case of the preferences for different study strategies, researchers developed items that described the deep and surface strategies and investigated how these items group in two or four-factor solutions. However, recent developments in the study of the complex phenomena used an alternative perspective to explain the shared variance of a set of items that describe a particular phenomenon.

The network psychometrics approach (Epskamp et al., 2018a) is based on the similarities between a statistical physics model (i.e., the Ising model) and the multi-dimensional items response theory models (MIRT models). Network psychometrics view item responses as inter-dependent variables that interact and reinforce each other, thus offering new perspectives regarding their shared variance. Costantini and Perugini (2017) described these new perspectives as follows.

Firstly, the network perspective assumes that complex behavior is an emergent phenomenon that results from the interaction of its constituent elements (Costantini & Perugini, 2017; Fonseca-Pedrero, 2017). In the case of the approaches to learning, network analysis does not treat various strategies and motives as interchangeable (as they are treated in the latent variables approach) but focus on their inter-dependency (i.e., their relationships). Secondly, the network perspective describes the specific role of each component in the emergence of the entire phenomenon (Costantini & Perugini, 2017). Based on the comparison of different relations between the strategies and motives that describe the preference for a particular study strategy, a network perspective should
provide evidence on the strongest and the weakest relations between the elements that constitute a preference for a particular study strategy. For example, the network analysis could compare the relations between study interest and the deep learning strategies, with the relations between study satisfaction and the deep learning strategies. Finally, network analysis provides evidence regarding the role of each constituent element in the emergence of the phenomenon, through the estimation of centrality indices (Costantini & Perugini, 2017). For example, recent network analysis found that the most central features of trait anxiety are i) the presence of intrusive thoughts and ii) the resistance of disappointments in one’s mind (Heeren et al., 2018). These two central elements are considered activators for the entire network of thoughts, feelings, and beliefs that are specific for anxiety. Using a network perspective, we could reach similar conclusions in the case of the approaches to learning.

**The present study**

We used the network perspective to analyze students’ preferences for study strategies. We analyzed the relationships between the items that describe strategies and motives for the deep approach and for the surface approach to identify the central elements that have the potential to activate or deactivate this network. Also, we investigated the stability of this network considering three factors: students’ gender, their academic discipline, and academic year.

**Method**

**Participants**

At the West University of Timișoara (WUT), the top management adopted an institutional development project (Ilie et al., 2020). The project team aimed to promote student-centred forms of learning across the entire university through one quality assurance system including research studies, learning and teaching programs for academics and teaching awards. As a part of this project, the present study was also approved. In the approval stage, the project proposal had to pass evaluations from several perspectives (e.g., financial, feasibility, expected impact), which also included an ethics evaluation. In particular, the present study was evaluated by the Ethic Committee of the Department of Teacher Training. Participants were 5357 students (76.96% female, mean age = 21.01 years old) from two Romanian universities (Table 1). They attended various specializations, which we classified in 4 categories (Becher, 1989): ‘pure hard’ (N = 996) – Chemistry, Biology, Geography, Mathematics, and Informatics; ‘applied hard’ (N = 417) – Medicine; ‘pure soft’ (N = 1908) – Linguistics, History, and Theology; and ‘applied soft’ (N = 2036) – Law, Administrative Sciences, Economy and Business Administration, Physical Education and Sports, Sociology, Psychology, Educational Science, Political Sciences, Philosophy, and Communication Sciences.

The Centre of Academic Development (CAD) of WUT offers yearly instructional development programs for academics. Between May 2017 and December 2018, the academics that attended the CAD programs were asked to facilitate the application of the R-SPQ-2F (Biggs et al., 2001) at one of their classes. Thus, the instrument was completed by
Table 1. Sample characteristics.

|                          | Hard disciplines | Soft disciplines |
|--------------------------|------------------|------------------|
|                          | Pure hard (N)    | Applied hard (N) | Pure soft (N) | Applied soft (N) | Total |
| Gender                   |                  |                  |               |                  |
| Female                   | 684              | 294              | 1643          | 1502             | 4123  |
| Male                     | 308              | 123              | 258           | 511              | 1200  |
| Not specified            | 4                | 0                | 7             | 23               | 34    |
| Age                      |                  |                  |               |                  |
| Mean                     | 20.36            | 21.29            | 20.73         | 21.49            | 21.01 |
| Range                    | 18–46            | 18–44            | 17–48         | 17–58            | 17–58 |
| Not specified            | 4                | 0                | 6             | 25               | 35    |
| Academic degree          |                  |                  |               |                  |
| Bachelor                 | 880              | 414              | 1820          | 1791             | 4905  |
| Master                   | 62               | 2                | 64            | 171              | 299   |
| PhD                      | 1                | 1                | 1             | 11               | 14    |
| Not specified            | 53               | 0                | 23            | 63               | 139   |
| Academic year            |                  |                  |               |                  |
| First-year               | 468              | 75               | 706           | 1048             | 2297  |
| Second-year              | 273              | 78               | 559           | 400              | 1310  |
| Third-year               | 187              | 118              | 583           | 460              | 1348  |
| Fourth-year              | 0                | 143              | 6             | 10               | 159   |
| Postgraduate             | 28               | 1                | 36            | 78               | 143   |
| Not specified            | 40               | 2                | 18            | 40               | 100   |
| Total                    | 996              | 417              | 1908          | 2036             | 5357  |

Measure

We collected responses by using R-SPQ-2F (Biggs et al., 2001). The R-SPQ-2F assesses deep learning and surface learning through two corresponding scales and two subscales (i.e., motives and strategies) for each approach. The instrument has 20 items and collects answers through one 5-point Likert scale (from never/only rarely true of me to always/ almost always true of me). We presented the details of the adaptation process of the R-SPQ-2F in the First supplemental material.

Data analyses

We used the recommendations for conducting network analysis provided by Costantini et al. (2015) and analyzed our dataset using several R packages. Our network analyses involved four steps: network estimation (i.e., estimation of the Graphical Gaussian Model), node centrality (i.e., estimation of the importance of each R-SPQ-2F item), network stability (i.e., we bootstrapped 95% confidence intervals for all edges and all centrality indices), and network replication (i.e., we compared the networks of subsets of participants). We present details of the data analysis in the Second supplemental material.
Results

Comparative analyses yielded small differences between our sub-samples (Table 2). Although the differences were statistically significant because of the large sample, the largest standardized mean difference was smaller than $d = .13$ (for the Deep approach), or smaller than $d = .30$ (for the Surface approach). According to Cohen (1988), these effect sizes can be considered small and have little practical importance.

Network estimation

Figure 1 represents the EBIC-LASSO network based on the regularized partial correlations between the R-SPQ-2F items. The R-SPQ-2F items clustered in two groups that correspond to the two approaches to learning (i.e., surface and deep). Regarding the surface learning items, learning things by rote without understanding (SS8) is strongly related to the idea that memorizing key sections is a better success strategy, as compared with understanding them (SM11). Although we did not assume causal relations in our network analysis, the relationship described above is interesting because it shows a strong association between a motivation (SM11) and a strategy (SS8). Another strong

| Variables     | Categories  | Deep learning approach | Surface Learning Approach |
|---------------|-------------|------------------------|---------------------------|
| Gender        | Female      | 3.11 (.72)             | 1.93 (.92)                |
|               | Male        | 3.01 (.79)             | 2.13 (.98)                |
| Study Year    | 1st year    | 3.01 (.70)             | 1.94 (.95)                |
|               | 2nd year    | 3.10 (.73)             | 1.88 (.91)                |
|               | 3rd year    | 3.11 (.76)             | 2.16 (.94)                |
| Study program | pure hard   | 3.07 (.79)             | 1.99 (1.01)               |
|               | applied hard| 3.11 (.65)             | 2.19 (.70)                |
|               | pure soft   | 3.09 (.72)             | 1.98 (.94)                |
|               | applied soft| 3.09 (.73)             | 1.94 (.94)                |
association between motivation and strategy is the relation between the utility to learn materials that are not likely to be in the examination (SM19) and the fact that lecturers should expect students to invest less studying time in materials that won’t be included in the examination (SS16). Finally, another strong association that is worth mentioning is between passing while doing as little work as possible (SM3) and keeping the work to the minimum because the course is not interesting (SM7).

Regarding the deep learning items, we found more numerous strong partial correlations, as compared with the number of strong associations between the surface learning items. We found strong relations between working hard because the material is interesting (DM13) and spending free time to find out more about interesting topics (DS14). In turn, DS14 is strongly related with DS6 (I find most new topics interesting and often spend extra time trying to obtain more information about them), and D6S is associated with the idea that any topic can be in highly interesting one the students ‘gets into it’ (DM5). Other strong associations were between deep learning items that involved a feeling of satisfaction (DM1-DS2).

**Node centrality indices**

Figure 2 presents the centrality indices for each node/item and their standardized values. The most central node is DS14 (I spend a lot of my free time finding out more about interesting topics which have been discussed in different classes), which had the highest level of all three centrality measures (i.e., strength, closeness, and betweenness). The second node in terms of centrality importance is an item that describes the motivation for surface learning (i.e., SM7 I do not find my course very interesting, so I keep my work to the minimum). This item is strongly connected with the third note in terms of centrality importance (i.e., DM13 I work hard at my studies because I find the material interesting). Altogether, centrality indices suggest that the student’s interest-to-effort ratio is a communality of the most central nodes.

![Figure 2](image_url)
Network stability

We assessed network stability using bootstrapping procedures to estimate the stability of the centrality indices and to estimate the accuracy of the edge values (Heney, 2018). Regarding edge accuracy estimation, we used the bootnet R package (Epskamp et al., 2018b) to compute the 95% confidence interval for each edge. The results of the edge accuracy estimation are presented in Figure 3.

Because the conclusions based on centrality indices are equally important as the analysis of network edges, we also estimated the stability of these indices using the correlation stability algorithm implemented by the bootnet package (Epskamp & Fried, 2018). We used the person-dropping bootstrap procedure that removes ten different proportions of random respondents from the dataset (i.e., proportions between 5% and 75% of the respondents), re-computes all centrality indices and correlates the new centrality indices with the initial solution. For each proportion, the algorithm conducted around 100 estimations. The results indicated that our centrality indices are very stable: even if we drop 75% of our sample, the strength centrality indices of these subsamples still correlate at $r = .70$ with the initial values. If we drop 59.4% of our sample, we still obtain similar centrality indices in the case of the betweenness centrality index, and the case of the closeness centrality index. Simulation studies conducted by Epskamp and Fried (2018) suggested that drop-percentages above 50% indicate good stability of the centrality indices. Therefore, we can conclude that our centrality indices are stable.

Network replicability

We were interested in investigating the replicability of our network. Following the analytic approach used by Fried et al. (2018), we utilized the NetworkComparisonTest package (van Borkulo et al., 2017) to compare the networks.

We investigated whether the network estimated on a female subsample ($N = 4123$) is similar to the network estimated on a male subsample ($N = 1200$). We found that the values of the edges in these two networks are strongly correlated ($\rho = .54$), and only 2 out of 190 edges were significantly different from one network to another. The centrality indices of the two networks (see Third supplemental material) are also strongly correlated ($\rho = .838$). Therefore, we can conclude that the network is invariant on these two subsamples.

We analyzed whether the network is replicable across the three undergraduate years; therefore, we estimated the network for 1st-year students ($N = 2297$), 2nd-year students ($N = 1310$), and 3rd-year students ($N = 1348$). The edges of the three networks were very strongly correlated ($\rho = .786$, between the 1st-year students and the 2nd-year students; $\rho = .833$ between the 1st-year students and the 3rd-year students; $\rho = .775$ between the 2nd-year students and the 3rd-year students). Regarding the differences between the edges of the three networks, we have found five significantly different edges between the 1st-year and the 2nd-year network, six significantly different edges between the 1st-year and the 3rd-year network, and five significantly different edges between the 2nd-year and the 3rd-year network. The centrality indices of the three networks (Table A, supplemental material) were also strongly correlated ($\rho = .876$, between the 1st-year students and the 2nd-year students; $\rho = .746$ between the 1st-year students and the 3rd-year students; $\rho = .875$ between the 2nd-year students and the 3rd-year students).
Figure 3. Bootstrapped confidence intervals of estimated edge weights.

Note: The black line indicates the bootstrapped mean values of the confidence interval, the red line indicates the sample values, and the gray area the 95% confidence intervals.
=.805 between the 2nd-year students and the 3rd-year students). Thus, we can conclude that the three networks are not different, although they are estimated on students from different study years.

We grouped our respondents into four groups based on their study specialization (pure hard, applied hard, pure soft, and applied soft – Becher, 1989), and we estimated different networks for each category. Our results suggested that the four networks are similar in terms of centrality indices (i.e., the correlation values of their centrality indices are $\rho > .65$), and in terms of edge strengths (i.e., more than 95% of the edges were not statistically different).

**Discussion**

The traditional approach assumed the existence of latent variables to explain the correlations between strategies and motivations that constitute students’ preferences for learning approaches. Recent developments suggested that the covariances between human behaviors can also be interpreted using a network perspective (Epskamp et al., 2018a). From a network psychometrics perspective, deep and surface learning strategies and motives are interconnected and interrelated, and their co-occurrence can be better understood if we analyze their relationships using a graphical LASSO network of the R-SPQ-2F (Biggs et al., 2001) items.

Our results suggested that students’ preferences for learning approaches can be understood as a dual network: a network formed by items that describe the surface motives and strategies, and a network formed by items for deep motives and strategies. Based on the network analysis, we can investigate how these two learning approaches are connected. In our graphical LASSO network, we identified two negatively associated central nodes, one for each type of process (i.e., DM13 and SM7). A commonality of the two items is that they both emphasize the student’s interest in the learning material. This finding is particularly important because it suggests that students’ interest has the best potential for activating one or another part of the network. This finding is convergent with the conclusions of previous studies. For example, Coertjens et al. (2016) reported that students who showed a high level of interest in the course that they attended also reported a low level of surface learning. Moreover, students who reported a higher level of surface learning declared that their interest decreased across the semester. From a network perspective (Costantini & Perugini, 2017), the presence of an interesting learning material activates these central nodes, and it is likely to activate other nodes directly, which in turn activates other nodes. Consequently, the entire network will be activated, and we will observe a preference for deep learning (in the case of high levels of interest) or a preference for surface learning (if the interest level is low). Regarding the nodes that have the strongest connections with the central nodes, the surface process items include ‘doing as little work as possible’ (SM3) and ‘it is unnecessary to do anything extra’ (SS12), while the deep process items refer to ‘spending a lot of free time finding out more’ (DS14). This suggests that surface and deep learning might result from an interest-to-effort ratio: interesting materials that are invested with extra time are also be understood in a deep manner, while uninteresting materials involve little effort and time, and are associated with surface learning.

Our results are convergent with previous research on motivation for learning and workload in higher education, carried out in the general context of students’
approaches to learning. For example, Kyndt et al. (2011) reported that students’ motivation for learning has two effects on their approaches to learning. A direct effect, in which autonomous motivation (i.e., studying out of interest or personal valuing) is positively related to a deep approach to learning and negatively related to a surface approach. An indirect effect, in which the impact of students’ autonomous motivation on their approaches to learning is mediated by the students’ perceptions of workload. When students perceived a low workload, no significant relationship between motivation and students’ approaches to learning was reported. In a high workload context, a significant and positive relationship between autonomous motivation and deep learning was found. Also, previous research highlighted that students’ perception of workload is affected by their interest in the topic (e.g., Chambers, 1992; Kyndt et al., 2014). Indeed, students with a high level of interest are more likely to perceive the workload as acceptable. Moreover, Baeten et al. (2010) indicated that the perceived heavy workload is correlated to the adoption of a surface approach to learning. Complementary to this, Kyndt et al. (2011) reported an appropriate workload as having a positively significant correlation with a deep approach to learning when students are involved in a complex task.

In our comparative analyses, the networks estimated on different sub-groups of students were very similar. This finding suggests that the emergence of students’ preferences for a learning approach involves similar processes, regardless of gender, year of study, or specialization. This is important because it suggests that any potential differences between these categories of students cannot be attributed to different emerging processes, but to different situational cues that have the potential to activate or to deactivate the network. Previous studies (e.g., Geitz et al., 2016; Smith & Miller, 2005) highlighted that the variables mentioned above (i.e., students’ gender, year of study, or specialization) have a significant impact on students’ preferences for learning approach. At the same time, other research studies reported opposite findings (e.g., Lake & Boyd, 2015; Lietz & Matthews, 2009). Our results complete this picture because they highlighted that these categories of learners (e.g., male, female, first year, second year, etc.) decide to adopt a specific approach of learning (similar or not) using the same decision-making process (i.e., an interest-to-effort ratio).

**Implications for practice**

One main challenge of higher education is to stimulate students towards adopting a deep approach to learning. Our results suggested that students’ interest (Schraw & Lehman, 2001) and workload (Kember, 2004) have a central role in defining the students’ preferences for a learning approach. Therefore, attempts to increase students’ interest and/or to design tasks with an appropriate workload could be of particular importance for educational practices in university. Several ideas for such suggestions can be found in the literature concerning workload (e.g., Chambers, 1992; Kyndt et al., 2011, 2014) and students’ interest in learning (e.g., Renninger & Hihi, 2011; Schraw et al., 2001).

First, one could use methods that promote students’ behavioral activity in the learning process. Several teaching methods that sustain students’ engagement in learning have been advanced in the literature (e.g., problem-based learning – Dochy et al., 2003; discovery learning – Mayer, 2004). One main aim of these methods is to promote deep learning
(Mayer, 2004). However, research studies reported mixed results. For example, using problem-based learning was not an effective approach when students perceived a high workload (Nijhuis et al., 2005). Therefore, it seems that even when student-centred methods are used, teachers should pay particular attention to promote students’ interest in learning and manage students’ perceptions of the workload.

Second, one could offer meaningful choices to students. It seems providing students with the possibility to redefine their learning task increases the students’ interest and helps them to manage the workload (Cordova & Lepper, 1996; Patall, 2013). An explanation that could be advanced for this effect of choices is that students tend to choose what could satisfy their curiosity (Shirey, 1992). According to Shin and Kim (2019), satisfying one’s curiosity contributes to the development of individual interest.

Third, one could highlight the relevance of the content and/or the task for the students. Teachers could use different techniques to increase the relevance of their content or their task such as reflection on task value, well-structured content, or clearness of demands upon students (Kyndt et al., 2014; Renninger & Hihi, 2011). In science courses, Hulleman and Harackiewicz (2009) implemented an intervention in which they encouraged students to make links between what they were learning in their courses and concrete aspects of their lives. The authors reported that students who initially presented low success expectations increased their interest and also course grades.

Finally, one could use mixed assignments between workload and task complexity. Kyndt et al. (2011) concluded that ‘it is important to find the balance between asking enough of students to keep them motivated and not asking too much so that they don’t get discouraged by the demands placed upon them’ (Kyndt et al., 2011, p. 147). The authors proposed these mixed assignments in which when the workload is higher, the task complexity is kept at a low level and vice versa. For example, one teacher aims to assess their students’ level of understanding of the four-phase model of interest development (Hidi & Renninger, 2006). In this case, high task complexity and low workload could be described as follows: students were asked to analyze an actual behavior (described in one-page case) by using the four-phase model of interest development. On the opposite side, low task complexity and high workload could be that in which students must respond to more than ten questions about the same model of interest development.

**Limitations and implications for future research**

Our findings have some limitations that should be addressed by future research studies. Our analyses are based only on the items of R-SPQ-2F (Biggs et al., 2001). Researchers should conduct similar analyses on a larger pool of items, that will include items from the R-SPQ-2F (Biggs et al., 2001) and items from other similar scales (e.g., the Approaches and Study Skills Inventory for Students – Tait et al., 1998; the Learning and Studying Questionnaire – Entwistle et al., 2003). Christensen et al. (2018) estimated the network of four inventories that assessed the openness to experience from slightly different perspectives (e.g., the Big Five perspective, the HEXACO perspective) and found an additional higher-order factor that was not previously known in the literature. Similarly, a network analysis on a larger pool of items that describe students’ approaches to learning could provide additional insights regarding this phenomenon.
Network estimation is based on cross-sectional data. Therefore, the results presented should not be interpreted as causal evidence, but as cues regarding the probable evolution of the network nodes. Future studies should investigate these cues using longitudinal designs that will differentiate between within-person evolutions of the network and between-person evolutions of the network, using statistical approaches that are already available (see Epskamp et al., 2018b). In addition, future research studies should use controlled trials to investigate whether the preference for a deep learning approach can be enhanced by interventions aimed at increasing students’ interest in the courses. If they prove successful, these interventions will provide causal evidence regarding the central role of student interest in determining the preference for a deep learning approach.

In the present study, we investigated the network replicability by considering only three variables (i.e., students’ gender, year of study, and specialization). Because previous research presented that students’ learning approach could be influenced by more variables (Baeten et al., 2010; Lindblom-Ylänne et al., 2019), future studies should investigate the network replicability considering variables such the learning environment, students’ self-efficacy beliefs or self-regulation skills.

Conclusions

This study reported that the interest-to-effort ratio is the central students’ behavior pattern through which they develop their preference for a learning approach. This behavior pattern seems to be stable across different contextual variables (i.e., students’ gender, academic year, and specialization). Therefore, we hope that the workload and students’ interest will receive more attention in pedagogical training initiatives dedicated to academics. Also, our study presented an invitation for researchers to use the network psychometrics perspective to investigate students’ approaches to learning.

Disclosure statement

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