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Explaining trace-based learner profiles with self-reports: the added value of psychological networks

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Structured abstract

Background. Learner profiles detected from digital trace data are typically triangulated with survey data to explain those profiles based on learners' internal conditions (e.g., motivation). However, survey data are often analysed with limited consideration of the interconnected nature of learners' internal conditions.

Objectives. Aiming to enable a thorough understanding of trace-based learner profiles, this paper presents and evaluates a comprehensive approach to analysis of learners' self-reports, which extends conventional statistical methods with psychological networks analysis.

Methods. The study context is a massive open online course (MOOC) aimed at promoting physical activity (PA) for health. Learners' (N=497) perceptions related to PA, as well as their self-efficacy and intentions to increase the level of PA were collected before and after the MOOC, while their interactions with the course were logged as digital traces. Learner profiles derived from trace data were further examined and interpreted through a combined use of conventional statistical methods and psychological networks analysis.

Results and Conclusions. The inclusion of psychological networks in the analysis of learners' self-reports collected before the start of the MOOC offers better understanding of trace-based learner profiles, compared to the conventional statistical analysis only. Likewise, the combined use of conventional statistical methods and psychological networks in the analysis of learners' self-reports before and after the MOOC provided more comprehensive insights about changes in the constructs measured in each learner profile.

Major takeaways. The combined use of conventional statistical methods and psychological networks presented in this paper sets a path for a comprehensive analysis of survey data. The insights it offers complement the information about learner profiles derived from trace data, thus allowing for a more thorough understanding of learners' course engagement than any individual method or data source would allow.

Keywords: Learning analytics, learner profiles, trace-data, self-reports, psychological network analysis

Practitioner Notes

What is already known about this topic:

- Researchers have made extensive use of data from online learning platforms – often referred to as learning trace data – to understand how learners engage in online learning activities.
- Surveys are often used to gather information about learners' motivation, perceptions, and other internal factors, to complement the insight gleaned from learning traces and thus create a more complete picture of the learning behaviour.
- When analysing survey data, the focus is usually on individual factors without considering how different factors are connected and affect one another.
- Psychological networks analysis is a novel analytic approach to studying complex phenomena both in psychology and education.

What this paper adds:

- The paper uses psychological networks as a method for examining mutual relations among learners' internal factors (e.g., motivation, perceptions) measured through self-reports before and after a course.
- By combining conventional statistical analysis of self-reports with psychological networks analysis, the paper develops a comprehensive picture of learners' internal factors measured through self-reports, one that accounts for both individual and interconnected nature of those factors.
- This comprehensive approach to information extraction from surveys allows for better understanding of trace-based learner profiles, that is, profiles mined from data about learners' interaction with online learning activities.

Implications for practice and/or policy:

- The presented method paves a way for a comprehensive analysis of the data collected from learners through surveys.
- It helps us gain a better understanding of learners' engagement with online learning activities.
- It can advance the evaluation of digital educational programs that aim to encourage changes in health-related behaviour.

1. Introduction

Detection of latent learner groups or profiles through analysis of learning trace data (i.e., data generated as a by-product of learners' interactions with digital systems and tools) has received much attention in learning analytics research (see Section 2.1). Such profiles, typically identified through unsupervised statistical learning methods, capture a specific pattern in learning behaviour that characterises a particular group of learners. Several studies have shown that trace-based learner profiles are associated with overall course or program performance (e.g., Jovanovic et al., 2017; Matcha et al., 2020b; Sun & Xie, 2020) and / or instructional interventions (e.g., Matcha et al., 2019). Still, such learner profiles are limited to the observable and trackable learning activities within a digital learning environment and thus only allow for answering the question of *how* learners approached their learning tasks, but not the question of *why* they behaved in this way. For a more comprehensive understanding of a learning behaviour, data about the learners' internal conditions (e.g., perceptions, intentions, motivation) are needed (Tempelaar et al., 2017; Jovanovic et al., 2021, Lim et al., 2021).

Self-reports in the form of surveys, often administered at the beginning and / or at the end of a course, are sometimes used to complement learning traces and enrich or validate trace-based learner profiles with data about learners' internal conditions. In particular, survey data have been used to triangulate trace-based measurements to help interpret the detected trace-based learner profiles (e.g., Matcha et al., 2020a; Sun & Xie, 2020) or simply to examine connections between the profiles derived from traces and those measured through self-reports (e.g., Gašević et al., 2017; Henrie et al., 2018). Furthermore, triangulation of learners' trace and survey data was used for a nuanced evaluation of a pedagogical intervention, allowing researchers to differentiate between the intervention's effect on supporting students to complete the current task (identified from trace data) vs. enabling students to develop a new skill (measured with survey data) (e.g., Pogorskiy & Beckmann, 2022). In addition, recently emerging approaches to validation of trace-based measurements of nuanced learning constructs (e.g., profiles based on micro-level self-regulated learning processes (Saint et al., 2020)) rely on learners' self-reports as their key data source (e.g., Fan et al., 2022b).

The existing studies that leveraged self-reporting surveys to interpret or validate trace-based learner profiles, typically analysed the survey data using conventional statistical approaches. For example, descriptive statistics, correlation analysis, and/or between-subjects statistical tests were often used to compare trace-based learner profiles based on constructs derived from survey items (e.g., cognitive and emotional engagement in (Henrie et al., 2018) or achievement goal orientation in (Gašević et al., 2017; Sun & Xie, 2020)). Similarly, studies that evaluated effects of a pedagogical intervention by using pre- and post-intervention surveys, typically analysed the collected self-reporting survey data with descriptive statistics and within-subjects statistical tests (e.g., Melero et al., 2015; Srivastava et al., 2022) or analysis of covariance (e.g., Pogorskiy & Beckmann, 2022), to examine effects of the intervention.

While these methodological approaches to analysis of data collected through self-reporting surveys have led to relevant insights in numerous educational research studies, they also have certain limitations. The one of relevance to the current paper is that responses to individual survey items or groups of items measuring the same construct (e.g., set of items measuring cognitive engagement) were often analysed individually, that is, with limited - if any - consideration of relations among responses to distinct items or among constructs measured by distinct item groups. For example, Matcha et al. (2020a) used students' responses to a personality traits survey to better understand learner profiles derived from learning trace data. In particular, the researchers examined how predictive the personality traits were of each profile, without considering mutual relations of the traits. However, personality traits emerge from mutually related personality dimensions (Cramer et al., 2012), and it is likely that more could have been learnt if relationships among traits were explored. In general, data collected through self-reports for the purpose of better understanding or validating trace-based profiles, relate to students' internal factors (e.g., motivation, perceptions, opinions, affective states), which are interconnected and interdependent. To comprehensively explore and understand students' internal factors, it is important to examine those factors (and, therefore, self-reporting items that measure them) both individually and from the perspective of their mutual connections. This is in line with the system-level approach to studying phenomena of interest (Meadows, 2008), where the focus is not only on individual components it consists of, but also on how those components are organised and relate to one another.

Recent methodological advancement in psychometrics offers promising approaches to addressing the above-mentioned limitation of survey data analysis, when analysing trace-based learner profiles. Specifically, in this paper, we report on a study that used *psychological networks* to complement conventional statistical analysis of survey items with analysis of relationships among those items, with the ultimate objective of advancing interpretation of trace-based learner profiles. Psychological networks (Borsboom et al., 2021) were proposed as a novel methodology for the analysis of self-reporting items in a more interdependent way, that is, as a network of items that are associated with one another and where connections (edges in the network) between the items (network nodes) are as important as the items themselves.

The current study proposed and evaluated an integrative analysis of student data that originates from learning traces and self-reported surveys. By integrative, we mean an analysis that includes i) detection of learner profiles from trace data (i.e., digital traces about learning activities), and ii)analysis of survey data, using both conventional statistical methods and psychological networks, to facilitate interpretation of the identified learner profiles. . The objective of the later step is to glean comprehensive information from the students' survey responses, by examining not only survey items individually (conventional statistical methods), but also the items' mutual connections (psychological networks) and, in that way, allow for better understanding of trace-based learner profiles . To examine the feasibility and effectiveness of this approach, we apply it to the data collected in the context of a massive open online course (MOOC) that was aimed at raising awareness of and promoting the relevance of physical activity for health.

2. Background

2.1 Combined use of trace data and self-reports for learner profiling

Initial research efforts in learning analytics have been primarily based on a single data source, typically log data from a learning management system or a similar platform supporting blended or fully online courses. Rapidly, it became clear that a single data source is insufficient for achieving learning analytics objectives, that is, understanding and optimising learning (Siemens, 2013). For example, Tempelaar and colleagues (2017) noted that insights generated through analysis of learning log data were not sufficient for crafting pedagogically sound interventions since they were limited to the detection of behavioural patterns and did not allow for explaining why students displayed such patterns. Drawbacks, but of different types, were also reported in studies that relied on student self-report data as the only data source. In particular, such data is often associated with distinct types of response bias such as social desirability or inattentiveness (Ober et al., 2021) or bias that stems from incomplete and reconstructed memories (Zhou & Winne, 2012).

To overcome the limitations of single data source and establish stronger grounds for pedagogical interventions, Templaar et al. (2017) complemented the insights obtained from learning logs with dispositional data (e.g., learning motivation, attitudes, strategies) collected through a self-reported survey. In their more recent study, Tempelaar et al. (2021) proposed a comprehensive approach to the measurement of learners' engagement with online courses, which included a combined use of i) learning logs as the evidence of the students' learning behaviour, ii) self-reported surveys to measure students' learning motivation, attitude, and emotions, and iii) formative assessment scores. Their study strengthened the relevance and complementary nature of the three data sources. Similarly, Matcha et al. (2020a) leveraged personality traits measured through a pre-course survey to better understand study strategies derived from learning trace data within a MOOC. On the other hand, Gašević et al. (2017) examined the correspondence between students' achievement goals measured through a pre-course survey and study strategies derived from log data in a blended course. They reported a low level of correspondence between the two constructs, which was attributed to the subtle difference in the constructs measured; as previously posited by Zhou and Winne (2012): self-reports largely capture study intentions, whereas log data capture what students actually did (i.e., realised intentions). This is further supported by the findings of van Halema et al. (2020), who in addition to the complementary nature of trace and self-report data, also reported the diminishing capacity of self-reports to explain students' online learning behaviour as the course progressed, that is, as the learning behaviour became temporarily distant from the intentions expressed in self-reports.

More recently, Han (2023) examined the extent of alignment between the students' self-reports (conceptions, approaches, and perceptions) and indicators of engagement derived from learning trace data, in the context of a flipped classroom university course in China. Like the aforementioned study by Gašević et al. (2017), this one also found weak alignment between self-reports and trace data. On the other hand, the two kinds of data proved to be complementary in explaining the variance in students' academic performance. Ober and colleagues (2021) examined the connection of self-reported levels of engagement and indicators of engagement derived from traced data logged by an online assessment system; the context was a high school Statistics course. While the researchers found almost no correlation between self-reported levels of engagement and those derived from trace data, they have also reported that logged student traces allowed for broader and deeper understanding of student behaviour compared to what self-reports revealed.

Some research relied on real-time students' self-reports as a way of validating inferences derived from learning traces. For example, Fan et al. (2022b) proposed a systematic approach to validation of trace-based measurement of self-regulated learning (SRL). A key element of this approach is the use of think aloud data as a "reference point" for validating inferences drawn from learning traces regarding SRL processes. In another study, Salehian Kia et al. (2021) compared the insights obtained from trace-based indicators of distinct SRL phases with those collected from real-time students' self-reports (obtained as responses to micro-analytic questions during a learning task), to examine the extent and conditions these indicators and self-reported measures are aligned, that is, indicate the same SRL phase.

While each of the above studies has demonstrated benefits and challenges of combined use of learning log data and self-reporting data, it remains an open question if further gains in understanding behaviour patterns derived from learning logs, could be obtained through a more advanced and comprehensive analysis of the collected self-reports. To address this question, this paper presents a comprehensive approach to self-reports analysis, which advances the current practice of examining each construct measured through self-reports (e.g., motivation, perception, expectations) individually, towards analytics that examine mutual relations among those constructs, thus accounting for the interconnected nature of the measured constructs (i.e., learners' internal factors). To that end, we make use of psychological network analysis, a network-based approach that allows for examining mutual relations among self-report items, as discussed next.

2.2 Psychological networks in education research

Network-based methodologies have been increasingly applied in education research (Saqr et al., 2022a; Elmoazen et al., 2022; Fan et al., 2022c). Social network analysis (SNA) has been one of the main learning analytics methodologies for studying social relations and interactions in different learning settings (Chen & Poquet, 2022). More recently, Epistemic network analysis (ENA) has been used to capture and explore the interdependent and temporal nature of collaborative learning and problem-solving processes (Swiecki et al., 2020; Ferreira et al., 2022). The two kinds of network analytics have also been combined to enable a comprehensive analysis of collaborative learning (Gašević et al., 2019). Like SNA and ENA, psychological networks used in the current study allow for examining interdependencies among the studied entities. However, they differ from SNA and ENA both in the kinds of entities examined and the kinds of relationships modelled.

In a psychological network, nodes represent variables typically derived from a self-reporting instrument, whereas edges, that is, edge weights represent the strength of the associations between pairs of variables, which are estimated through a statistical method (Borsboom et al., 2021). Such networks were first introduced in psychology research to study complex psychological phenomena, e.g., in psychopathology (Epskamp et al., 2018a; Fried et al., 2018) and personality studies (Costantini et al., 2015; Costantini et al., 2019). As the field of psychology is their initial and still dominant application domain, these networks are often referred to as psychological networks.

In between-subjects psychological networks based on cross-sectional ordinal or continuous data - the kinds of networks that are the focus of this paper - edges often represent partial correlations between node pairs, that is, correlations between a pair of nodes (variables) after controlling for all the other variables in the dataset (Borsboom et al., 2021). This type of statistical model is known as Gaussian graphical model (GGM) (Epskamp et al., 2018). Partial correlations in GGMs are also referred to as conditional dependencies between variables: if two variables are connected in the resulting graph, they are dependent after controlling for all other variables, whereas the absence of an edge means that variables are conditionally independent. Such networks could be related to multiple regression models in the sense that the nodes (variables) that are connected to a particular node (variable) of interest are likely to be its significant predictors in a multiple regression model (Epskamp & Fried, 2018).

Psychological networks, in general, and GGMs in particular, are a fairly novel data analytic approach in the educational domain, as it was used in a relatively small number of learning-related studies. Among them, for example, Sachisthal et al. (2019) created and analysed a between-subjects network based on cross-sectional data about learners' interest in science, collected in the 2015 edition of the Programme for International Student Assessment (PISA). The nodes in the network corresponded to variables reflective of the learners' science interest, namely science enjoyment, knowledge, self-efficacy, value of learning science, and engagement with science. The objective was to examine mutual relations of these variables and identify those that were central to the students' interest in science and thus should be the focus of an intervention. Govorova et al. (2020) also used a psychological network approach to examine PISA data from 2018 assessments, focusing on the students' well-being. The network included variables related to cognitive, psychological, and social well-being of students as well as variables reflective of teaching style and school climate. The objective was to examine how the elements of well-being interact, and how they are associated with school-related factors. Abacioglu et al. (2019) used psychological networks, specifically between-subjects GGMs, to examine associations between teachers' multicultural approach and student motivation in classrooms with ethnic minority and majority groups. To understand commonalities and differences in classroom experiences of students from different ethnic groups, they created and compared networks of distinct ethnic groups, where each network included variables (nodes) reflecting students' motivation, general and ethnic victimisation at an individual and ethnic group level, ethnic background and identity, social integration, and the students' perceptions of the teachers' multicultural approach.

In addition to between-subjects networks based on cross sectional data, there are also temporal networks that allow for examining temporal relations among variables based on repeated measures data (Constantini et al., 2019). While such networks can reveal relevant causal relations among variables, they require longitudinal data and are typically used in idiographic studies as within-subjects networks (e.g., Fisher et al., 2017). Therefore, such networks are out of the scope of the current paper and interested readers are referred to, for example, (Prieto et al., 2022; Saqr & López-Pernas, 2021) to learn about the potentials of temporal within-subject networks in the educational domain.

To conclude this section, we note that psychological networks analysis has proven to be a promising analytics approach to studying complex phenomena both in psychology and education. Still, they have not been used for analysing students' self-reports collected before and after a course (i.e., an educational intervention, more generally), as an approach to improve understanding of trace-based learner profiles.

3. Research objectives and questions

The objective of this study is to examine the quality of insights about distinct trace-based learner profiles that could be obtained through a *comprehensive analysis* of self-reporting survey items. By comprehensive *analysis*, we mean here an analysis that includes *both* individual examination of survey items using traditional statistical methods and examination of the items' mutual connections using psychological networks analysis.

Towards the stated research objective, we formulate our first research question as follows:

RQ1: Whether and to what extent the inclusion of psychological networks in the analysis of learners' self-reports (i.e., responses to survey items) before the start of a course (i.e., an educational intervention, more generally) offers more comprehensive information, and thus better understanding, of learner profiles derived from learning traces, compared to the information offered by conventional statistical analysis of the same self-reports?

Simply put, we aimed at exploring if and to what extent the information obtained through psychological network analysis improves our understanding of the trace-based learner profiles beyond and above what traditional statistical analysis would provide. In addition, we wanted to examine if / how distinct trace-based learner profiles changed after the course (or an educational intervention, more generally), with respect to the constructs measured through a self-reporting survey. Hence, our second research question is defined as follows:

RQ2: Whether and to what extent the inclusion of psychological networks in the analysis of learners' self-reports (i.e., responses to survey items) before and after an educational intervention (e.g., a course) allows for better understanding of the effects of the intervention on distinct trace-based learner profiles?

More specifically, RQ2 aimed to examine to what extent the change (or lack of it) in the measured constructs, in distinct trace-based learner profiles, can be better understood by extending conventional methods for pre-post survey analysis with psychological networks, thus allowing for both individual and relational examination of the survey items.

4. Methods

We explore our research questions in the context of a MOOC that aims to educate people about the relevance of physical activity (PA) for health and offer practical guidance for including more PA into daily life. In particular, we wanted to examine if the learners' perceptions, self-efficacy, and intentions related to PA could help us interpret and understand learner profiles reflective of the ways the learners' interacted with the course activities (RQ1). In addition, we wanted to examine if / how distinct activity-based learner profiles changed their PA-related perceptions, self-efficacy, and intentions after the course (RQ2). To that end, we applied both conventional statistical methods (Section 4.4.1) and psychological network analysis (Section 4.4.2) to the survey items through which the learners (i.e., MOOC participants) expressed - before and after the MOOC - their perceptions related to PA, as well as their self-efficacy and intention to increase the level of PA.

4.1 Study context

The study context is the Sit Less Get Active MOOC, offered by the University of Edinburgh through the Coursera learning platform, since June 2016. It is aimed at raising awareness of the relevance of PA for health and offering practical guidance for increasing the level of PA in everyday life. The "core" part of the MOOC consists of three weeks of learning activities; then, over the period of six months after the completion of the core part, the participants would be sent weekly PA promotional messages and monthly PA promotional videos, to serve as nudges for remaining active.

The core part of the MOOC, which is in the focus of the current study, includes several kinds of learning activities, namely videos (5 videos per week), optional readings, quizzes, forum discussions, and assignments. The summative (i.e., graded) activities include two assignments and three quizzes, whereas the remaining quizzes (i.e., practice quizzes) have the role of formative assessment. The course schedule is flexible, meaning that after enrolling in the course, learners are free to engage with the course activities at their own pace.

Before engaging with the course activities, the course participants were asked to fill out a survey that, among other data, collected data about the participants' perceptions, self-efficacy, and intentions related to PA. The participants were asked to answer the same questions after completing the core part of the MOOC.

4.2 Data sources and the study sample

We collected learning trace data from the Coursera database of the Sit Less Get Active MOOC. In particular, with the course design in mind, we extracted the log data related to the participants' interaction with the course videos (*video_lecture* events), formative assessment (*practice_quiz*), forum discussions (*forum_task)*, summative assessment tasks (*exam*), and a range of optional / extra resources (e.g., optional readings about PA) that were provided to the participants (*optional_activity*).

The other data source were the surveys that the MOOC participants filled out before starting and after completing the core part of the MOOC. We refer to the former as the *baseline survey*, while the latter is referred to as the *follow-up survey.* In line with our research questions, in the current study, we considered only survey items related to the participants' perceived importance of PA, how they perceive their current level of PA, as well as their self-efficacy for and intention to be more physically active (Table 1). The survey items were based on the Theory of Planned Behaviour (Ajzen, 1991) and were used previously (Godino et al., 2014). Concern about PA was measured on a 10-point response scale that ranged from "Not at all" to "Very concerned". The other survey items were evaluated on a 7-point response scale whereby the responses ranged from "Strongly agree" to "Strongly disagree".

Table 1. Survey items used in the analysis of learner profiles

Node ID	Item label	Item text	Construct measured
1	More_PA_better_my_health	If I was more physically active in the next two months, it is likely that my health would improve.	Response efficacy
2	Social_expectations	Most people who are important to me would want me to be more physically active.	Subjective norm

3	PA_enough_stay_healthy	I do enough physical activity to stay healthy.	Perceived adequacy
4	Intend_more_PA	I intend to be more physically active in the next two months.	Intention to be more physically active
5	Confident_more_PA	I am confident I could be more physically active in the next two months if I wanted to	Self-efficacy
6	Concerned_current_PA	How concerned are you about your current level of physical activity?	Concern about PA
7	Important_more_PA	How important is it to you to increase your level of physical activity?	Perceived Importance of being more physically active

The study sample consisted of 497 course participants for whom the following criteria were satisfied:

i) They filled out both the baseline and the follow-up survey, and the follow-up survey was completed at least 21 days after completing the baseline. Twenty-one days was used as the minimum timespan between the two surveys considering that the core part of the MOOC lasted 21 days; in addition, some of the course activities required tracking one's PA over certain periods of time.

ii) They answered all items listed in Table 1, both in the baseline and follow-up surveys.

iii) Their interaction with the course was logged in the Coursera database. In particular, their logged traces included at least one event related to the engagement with any of the following resources: course videos, formative assessment, summative assessment, forum discussions, and optional materials. In other words, those who just logged into the learning platform without completing any learning activity were not considered.

4.3 Trace-based learner profiles

To identify learner profiles based on their interaction with the course resources, we applied a slightly modified version of the method proposed by Matcha et al. (2019). That method proved effective in several previous studies that identified and examined learner profiles from trace data (e.g., Matcha et al., 2020b; Fan et al., 2022a). In particular, the method consists of two steps: 1) identifying patterns in learning behaviour at the level of study sessions; the detected patterns are considered manifestations of the *study tactics* adopted by learners; 2) using the detected tactics to identify patterns in behaviour at the level of the overall course; thus identified patterns are reflective of the adopted *study strategies* and are used to characterise *strategy-based learner profiles*.

To apply the aforementioned method, for each participant in the study sample, we created time ordered sequences of logged learning events and split those sequences into the study sessions. Sessions were identified as consecutive sequences of learning events where the time distance between two consecutive events was below the set threshold. This threshold was chosen based on the analysis of the distribution of time gaps between consecutive events in the logged data (Jovanovic et al., 2019; Saqr et al., 2022b); in particular, 95th percentile of time gaps (26 minutes) served as the threshold. This way, 3682 sessions were identified.

In the first step, each study session was transformed into a numerical representation by feeding the corresponding chronologically ordered sequence of events to the First Order Markov Model (FOMM). The result produced by FOMM for each session included a transition matrix, that is, a matrix of probabilities of any learning event being followed by any other event. These matrices were then used as the input to the Expectation Maximisation (EM) clustering algorithm to identify groups of study sessions that were similar in terms of event sequences. We refer to thus identified latent session groups as study tactics. This first step was done using the implementation of FOMM and EM algorithms in the pMiner R package (Gatta et al., 2017). Note that FOMMs were created using sessions with at least two events, since for a session with one event only a transition matrix could not have been created (there were no transitions). Among the identified sessions, 480 (13%) consisted of one event only; these one-event sessions were not used for tactic detection, but were used in the next step for detecting strategy-based learner profiles.

In the second step, which was aimed at the detection of strategy-based learner profiles, the identified study tactics served as an input to a clustering algorithm. In particular, two kinds of features were computed for each study participant and fed to the Agglomerative Hierarchical clustering method (based on the Ward's algorithm): i) number of sessions in each tactic; the number of these features corresponded to the number of distinct tactics detected in step 1, while each feature represented the number of sessions of the given participant that 'belonged' to the given tactic; ii) number of 1-event sessions of the given participant. All features were log transformed as almost all were skewed. In particular, the $\ln(x + 1)$ transformation was applied, to avoid getting infinity in case of zero feature values. The number of clusters was determined by inspecting the dendrogram produced by the clustering algorithm and by comparing silhouette widths of different clustering solutions.

4.4 Analysis of survey data

The collected survey data required some pre-processing. In particular, a subset of variables (i.e., survey items) had to be transformed so that all have "the same direction", namely higher values denoting higher agreement with the statement. For example, the survey item "I do enough physical activity to stay healthy" (#3 in Table 1) is associated with a 7-point scale where 1 denotes strong agreement, whereas 7 denotes strong disagreement; the item was re-coded so that 1 denotes strong disagreement and 7 strong agreement. In addition, some variables (i.e., survey items) were based on a 7-point scale, while others used a 10-point scale; for the network analysis, all variables were rescaled to a common 7-point scale, which was chosen as the dominant scale among the survey items.

4.4.1 Traditional statistical analysis

To address our RQs, we first conducted traditional statistical analysis of individual survey items. Since the collected survey responses were not normally distributed, non-parametric tests were applied. In particular, in the context of RQ1, for each survey item, we applied the Kruskal-Wallis test to examine the differences among the learner profiles (identified using the method described in Section 4.3). To address RQ2, for each learner profile, we compared the responses on the baseline and the follow-up surveys using the paired Wilcoxon Sign Rank test. Considering the number of survey items (7) and thus the number of comparisons, we applied the Bonferroni correction to address the multiple testing issue. Thus, the corrected alpha value that was used for determining statistical significance was 0.0071 (=0.05/7). In addition, descriptive statistics (median, 1st and 3rd quartile) were computed separately for each learner profile, both for the baseline and the follow-up surveys. All these analyses were done using the *rstatix* R package (Kassambara, 2021).

4.4.2 Network analysis

The network analysis, required for both RQs, included four steps: network estimation, network inference, network stability assessment, and network comparison.

Network estimation. We needed to estimate two groups of networks: one group based on the data collected through the baseline survey and the other one based on the data from the follow-up survey. Each group included one network for each trace-based learner profile. Since our data were cross-sectional and ordinal and we wanted to model conditional dependence among the variables (survey items), the networks were modelled as Gaussian Graphical Models (GGMs) (Epskamp & Fried, 2018). Such networks are often estimated with Graphical Lasso, a method that uses regularization to avoid estimating spurious edges and has proven effective in estimating GGMs (Epskamp et al., 2018). However, we opted for Fused Graphical Lasso (FGL), a method based on Graphical Lasso that is recommended for jointly estimating networks across multiple groups that share some similarities but also present some differences (Danaher et al., 2014), as it was the case with our trace-based learner profiles. Joint estimation of multiple networks using FGL has several advantages over independent network estimates for distinct groups, among which particularly relevant to our study is that FGL allows for “simultaneously exploiting the similarities between groups without masking their differences” and thus “provides an elegant solution to the issue of network comparison” (Costantini et al., 2019, p.3).

We estimated networks using the FGL implementation in the EstimateGroupNetwork R package (Costantini et al., 2021). For each network group, the FGL algorithm was fed with polychoric correlation matrices, one for each trace-based learner profile. We opted for polychoric correlations since the collected survey data were ordinal in nature (see Section 4.2). To illustrate how the FGL algorithm transforms the input correlation matrices into networks (i.e., adjacency matrices the networks are based upon), we have included, in Section S1 of the Supplementary document, tables with three polychoric correlation matrices (each one corresponding to one trace-based learner profile) that served as the input to the FGL algorithm for building the three baseline networks, as well as the corresponding adjacency matrices the resulting networks are based on.

The FGL algorithm has two key regularisation parameters. One parameter (λ1) regulates network sparsity (larger λ1 values yield sparser networks), whereas the other (λ2) regulates the similarity of the networks estimated for different groups (higher λ2 values yield more similar networks). Both parameters were estimated using the *InformationCriteria* method and the *simultaneous* strategy, as implemented in the *EstimateGroupNetwork* package. The *InformationCriteria* method was selected to ensure methodological consistency with the procedure that evaluates network stability (discussed below), whereas the *simultaneous* strategy was chosen as it returns more accurate results (at the expense of longer computational time) (Costantini et al., 2021). Since the estimation method selected dense regularized networks and produced warnings to interpret the presence of low-weight edges with care, when interpreting the resulting networks, we considered only edges with weight above 0.1, to ensure high specificity, that is, to avoid false positives and overinterpretation (Epskamp et al., 2012). The threshold of 0.1 was chosen since the median edge weight in all estimated networks was in the 0.10 - 0.17 range.

The described network estimation process resulted in six psychological networks, that is, two networks for each trace-based learner profile: one network derived from the baseline survey data and the other from the follow-up survey. In all the networks, nodes correspond to survey items listed in Table 1, while edge weights represent partial correlations between the two adjacent nodes.

Network inference. We computed strength centrality indices for the estimated networks. Strength centrality for a particular node (variable) is defined as the sum of weights of the edges that connect the given node with its immediate neighbours and thus reflects how relevant a node (variable) is from the perspective of its potential effect on the related variables (Bringmann et al., 2019). In the context of the current study, strength centrality allows for identifying learners' internal factors (measured via the surveys) that have the highest potential to affect other measured internal factors. The rationale for restricting our analysis to strength centrality only is twofold: i) other centrality measures (e.g., betweenness and closeness) are often not reliably estimated (Epskamp & Fried, 2018), especially in small samples such as ours and ii) the meaning and interpretation of other centrality measures in psychological networks are questionable (Bringmann et al., 2019).

Network stability. To evaluate the stability of the estimated networks, we used the bootstrapping methods implemented in the *bootnet* R package (Epskamp et al., 2018). Since stability estimation methods for jointly estimated networks are (still) not available, we examined the stability of each network individually. Thus, the resulting stability estimates should be considered a lower bound for stability of the networks obtained with the FGL method (Fried et al., 2018). We used non-parametric bootstrap to get 95% confidence intervals for the estimated edge weights, whereas case-dropping bootstrap was used to assess the stability of the estimated strength centrality. The results for edge weight and strength centrality confidence intervals are reported in Sections S2 and S3, respectively, of the Supplementary document. It should be noted that the small sample size (of individual learner profiles) affects the stability of the estimated strength centrality measures, so the estimated strength centrality values need to be interpreted with caution.

Network comparison. To address our RQs, we needed to compare the baseline networks of distinct trace-based learner profiles (RQ1) as well as baseline and follow-up network pairs for each learner profile (RQ2). Due to the relatively small sample size of individual latent groups (learner profiles), we were not able to rely on statistical comparison of the estimated networks. On the other hand, the applied network estimation method, namely FGL, already considers similarities and differences of the distinct groups when doing the simultaneous network estimation for those groups; in particular, similarities are exploited for better estimates of common elements, while differences are not masked (Costantini et al., 2019). Thus, we relied on visual comparison of the networks (as was done by (Constantini et al. (2019) and (Richetin et al., 2017)). To ensure reliable interpretation of the plotted networks and their differences, we did the following:

- For each network comparison, the maximum edge weight was determined across the networks to be compared and was used in the network plotting function (*ggraph* of the same named R package) for scaling edge widths, so that the widths of all edges in the network plots were comparable.
- As stated in the part on network estimation, in each individual network, only edges with weight above 0.1 were plotted and interpreted.
- Only differences in edge weights that were greater than 0.065 were considered, to avoid overinterpretation. This threshold was chosen as the average Q1 edge weight value across all estimated networks and the rationale was to have at least a quartile difference to be considered notable.

In addition to the aforementioned *bootnet* and *EstimateGroupNetwork* R packages, *qgraph* package (Epskamp et al., 2012) was also used, primarily for plotting the networks.

5. Results

The adopted trace-based method for the detection of learner profiles (Section 4.3) resulted in three strategy-based learner profiles. In particular, we first (Step 1) identified three study tactics:

- Tactic 1 (Assessment-oriented): assessment-oriented sessions, dominated by summative assessment
- Tactic 2 (Learning-oriented): shorter sessions (than in other tactics), focused on learning and information gathering, as the sessions were focused on video watching, practise quizzes (i.e., formative assessment) and optional readings.
- Tactic 3 (Mixed): combined and roughly equal use of almost all course resources and activities throughout learning sessions; the only exception is engagement with forum tasks, which was only marginally present

In the second step, the following learner profiles were identified:

- Learner profile 1 (LP1): Low engaged, mostly browsing through diverse course resources (151 participants, 30.38%). This profile is characterised by low level of interaction with diverse course resources; the *Mixed* tactic is prominent, followed by the *Learning-oriented* tactic, whereas the *Assessment-oriented* tactic was practically absent.
- Learner profile 2 (LP2): Highly engaged, focused on learning and information gathering (177 participants, 35.61%). This profile has a high level of interaction with a variety of course resources and tactics; *Learning-oriented* tactic is particularly prominent, closely followed by the *Mixed* tactic, whereas the *Assessment-oriented* tactic was much less used.
- Learner profile 3 (LP3): Moderately engaged, committed to both information gathering and assessment (169 participants, 34.00%). This group had a moderate level of learning activity, with roughly equal use of all tactics.

Further information about the identified learning tactics and learner profiles is available in Section S4 of the Supplementary document[1].

5.1 RQ1: Interpretation of trace-based learner profiles through analysis of learners' initial self-reports

The results of Kruskal-Wallis tests showed no statistically significant difference across the learner profiles on any of the examined survey items (i.e., items listed in Table 1). The test results and descriptive statistics for all survey items are provided in Section S5 of the Supplementary document. On the other hand, a comparison of the psychological networks that were jointly estimated for the three learner profiles based on the baseline survey data offered information regarding the learner profiles and how they differed in their perceptions of PA, their self-efficacy for PA, and intent to engage in PA. The networks are presented in Figure 1, and the identified differences can be summarised as follows:

- Only in LP1, the expectations for being more physically active by one's close social circle (2) was positively connected to the intention to increase PA in the next two months (4), while also being negatively connected to the perception of doing enough PA to stay healthy (3). This suggests that in LP1, unlike the other two profiles, external motivation (social expectations in this particular case) played a role in orienting these participants towards being more physically active.. On the other hand, social expectations as external factors seemed not to be enough to motivate this group of participants to engage with the course considering that they had low and mostly superficial engagement with the course activities.

[1] Sequence distribution plots that show, for each tactic, the distribution of learning events at each time point in a session, are given in Section S4.1 of the Supplementary document; each plot depicts the pattern in learning event sequences that characterises the corresponding tactic. The details about the identified learner profiles - including descriptive statistics and plots showing distribution of features used for clustering - are available in Section S4.2 of the Supplementary document.

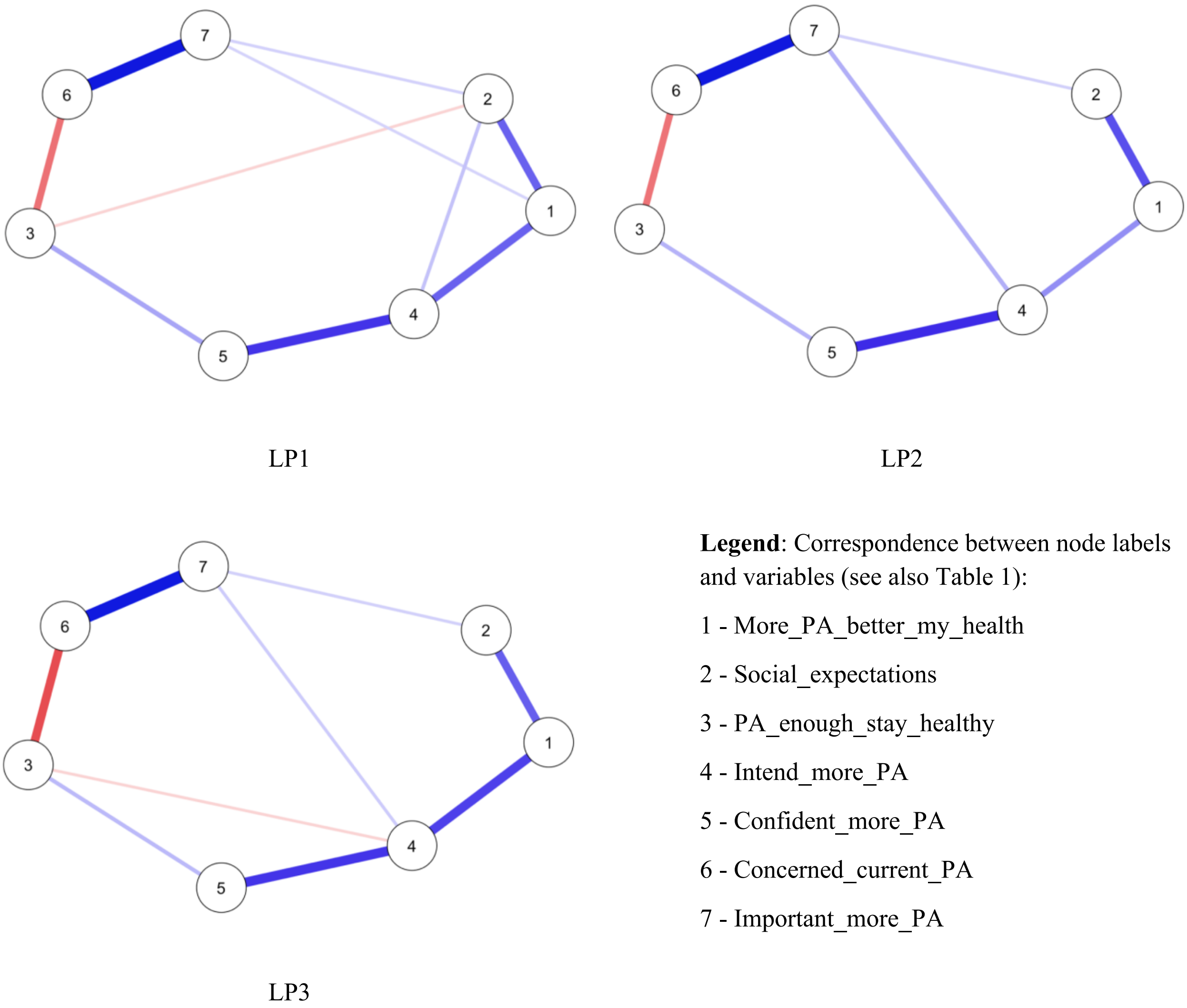


Figure 1. The networks (jointly) estimated for the three learner profiles based on the baseline survey responses. Edge thickness denotes the degree of association (i.e., conditional dependence); only edges with weight > 0.1 are plotted; blue edges represent positive, while red edges represent negative associations.

- Only in LP1, the perceived importance of increasing one's PA (7) was positively connected to the expectation that engaging in more PA would improve one's health (1). On the other hand, in LP2 and LP3, the perceived importance of being more physically active (7) was positively connected to the intention to increase PA in the next two months (4). This suggests that for LP2 and LP3, the perceived importance of increasing PA acted as a "stimulus" for increasing PA, whereas in LP1, it contributed to the recognition of the benefits that more PA would have on one's health, but did not seem to offer an impetus to modify their behaviour. This finding provides further explanation for the lower and often cursory engagement of LP1 with learning activities, compared to the other two learner profiles.

- A positive connection between the expectation that more PA would improve one's health (1) and the intention to engage in more PA in the next two months (4), was present in all three profiles, but differed in strength. Specifically, LP3 demonstrated the strongest positive connection between the expected health benefits of more PA and their intention to be more physically active, whereas in LP2, this connection was the weakest. In addition, only in LP3, the intention to be more physically active (4) was negatively connected to the perception of doing enough PA to stay healthy (3); in addition, the latter was in LP3 more strongly (negatively) connected to the concern for one's current level of PA (6). This suggests that LP3 had, in a way, two stimuli for engaging in more PA: 1) positive connection to the expectation about the benefits of engaging in more PA for their health, and 2) negative connection to the perception of doing enough PA to stay healthy (which was, in turn, affected by the concern for their current level of PA (6)). This finding sheds some light on the observed behaviour pattern of LP3 during the course, in particular, that it was the only profile that was not only interested in information gathering, but also in the evaluation of their fitness level and progress in advancing their PA.

The correlation-stability (CS) coefficient for strength centrality was 0.106, 0.339, and 0.408 for networks corresponding to profiles LP1, LP2, and LP3, respectively. These CS values indicate low stability of the strength centrality values for LP1 and medium stability for the learner profiles LP2 and LP3. Hence, the estimated strength centrality indices for LP1 needs to be interpreted with caution.

In the three networks, the same items were among the top 3 most central nodes, namely *Intention to increase one's P*A (4), *Concern for one's current level of PA* (6), and *Perceived importance of increasing one's PA* (7). This suggests that in the three learner profiles, the same set of variables had the largest potential to affect other PA-related variables. The strength centrality values are plotted in Figure 2 and reported in Section S3.1.1 of the Supplementary file.

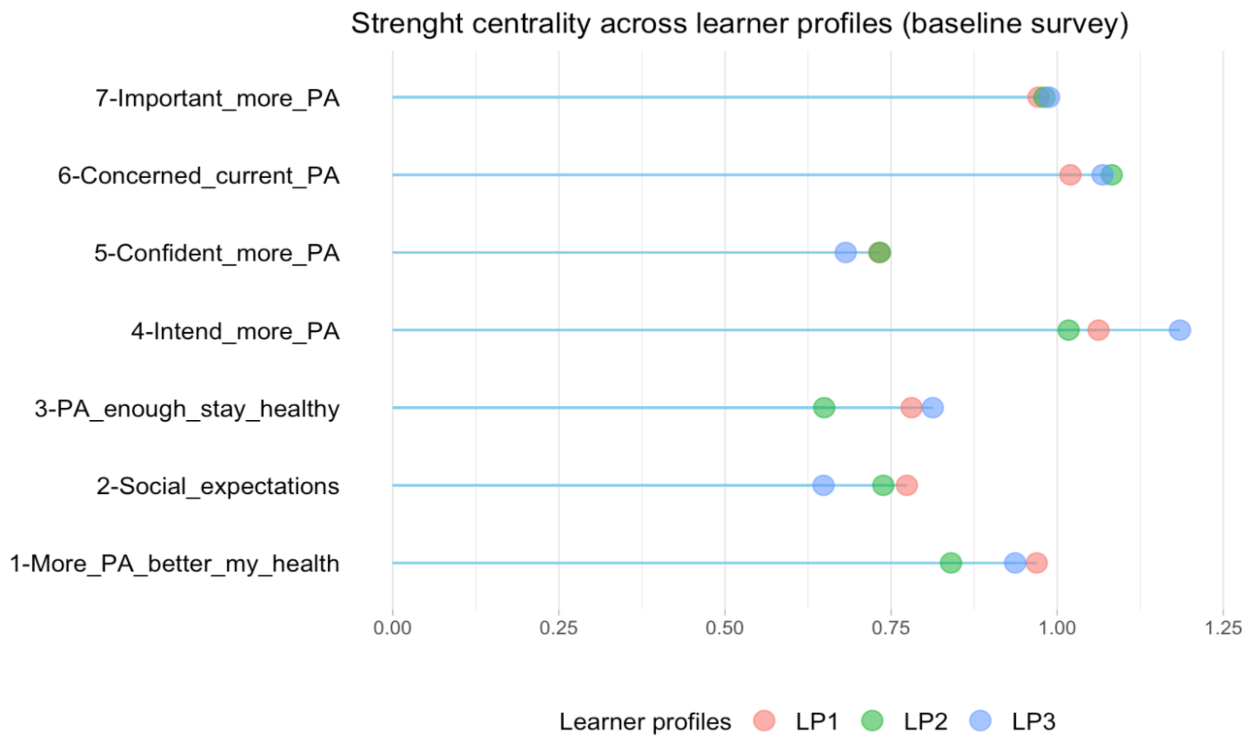


Figure 2. Strength centrality in the networks, estimated based on the baseline survey responses, for the three learner profiles

5.2 RQ2: Analysis of changes in perceptions, self-efficacy, and intentions related to PA

To address RQ2, we report, for each trace-based learner profile, the comparisons of the participants' responses to the baseline and follow-up surveys done using i) conventional statistical tests (i.e., Paired Wilcoxon Sign Rank test) and ii) psychological network analysis.

5.2.1 Learner profile 1

Having applied the Paired Wilcoxon Sign Rank test with Bonferroni correction to compare the responses to the baseline and follow-up surveys of the participants with LP1 profile, we identified significant differences, with moderate effect sizes, for two survey items. In particular, the perception of doing enough PA to stay healthy increased, whereas the concern for one's current level of PA decreased. The test results for these two items, including the descriptive statistics and effect size are given in Table 2, whereas the results for all the survey items are given in Section S6.1 of the Supplementary file.

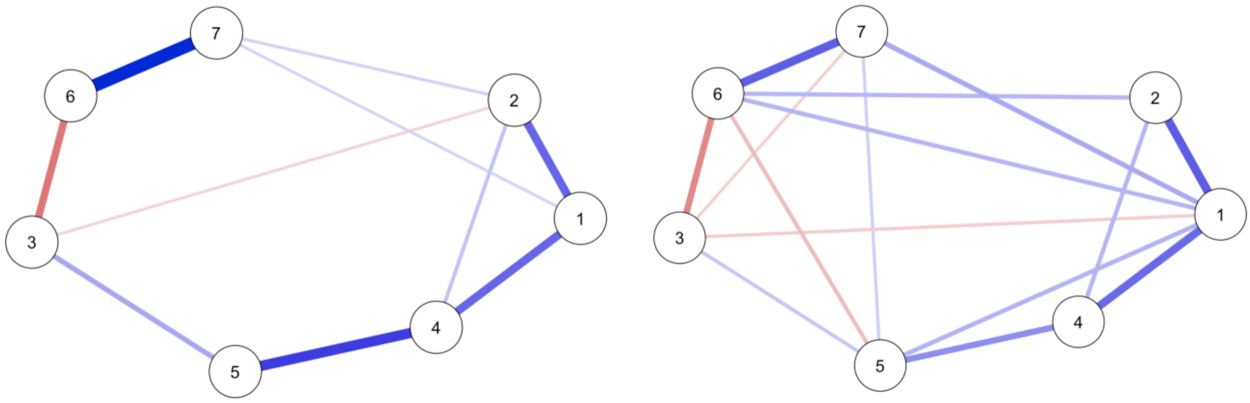
Table 2 Statistical comparison of individual items on the baseline and the follow-up surveys for each learner profile; only items with statistically significant change in their values are shown

Item	Baseline survey Mdn (25%, 75%)	Follow-up survey Mdn (25%, 75%)	W statistic	p-value	r
Learner profile 1					
PA_enough_stay_healthy	4 (2.5, 6)	5 (3, 6)	1461.5	< 0.0001	0.3770
Concerned_current_PA	7 (5, 9)	6 (4, 8)	4437.0	0.0004	0.3059
Learner Profile 2					
PA_enough_stay_healthy	4 (2, 5)	5 (4, 6)	1484.0	< 0.0001	0.5233
Concerned_current_PA	7 (6, 9)	7 (4, 8)	6260.0	< 0.0001	0.3395
Learner Profile 3					
PA_enough_stay_healthy	4 (2, 6)	5 (4, 6)	1004.5	< 0.0001	0.5453
Concerned_current_PA	7 (5, 8)	6 (3, 8)	5443.0	< 0.0001	0.3399
Confident_more_PA	6 (5, 7)	7 (6, 7)	1587.5	0.0055	0.2233

Figure 3 presents networks estimated from the baseline (a) and follow-up (b) survey responses of the LP1 learner profile. A comparison of the two networks, in terms of changes in associations among the examined PA-related variables, is given below.

The expectations for engaging in more PA by one's close social circle (2), as observed in the baseline survey, lost its positive connection to the perceived importance of increasing PA (7) and its negative connection to the perception of doing enough PA to be healthy (3). Instead, a positive connection to the concern for the current level of PA (6) has been established. The analysis of the baseline networks (Section 5.1) suggested that the role of social expectations for having more PA was the main distinguishing feature of this learning profile, compared to the other two profiles. After the course, social expectations show less prominence in framing one's perception of PA; instead, as discussed below, the course seems to have contributed to building LP1's intrinsic motivation to increase their PA levels.

A concern for one's level of PA (6) became positively connected with the expectation that engaging in more PA in the next two months would improve one's health (1), and the latter showed a stronger positive connection to the perceived importance of increasing one's PA (7). This might be considered a positive outcome of the course: raising one's awareness of the benefits of PA for one's health, so that the perceived relevance of PA comes from one's own understanding of its benefits, not only expectations of one's social circle.



(a) (b)

Figure 3. Networks estimated based on the responses of the LP1 group to the baseline survey (a) and the follow-up survey (b). The correspondence between node labels and variables:
1 - More_PA_better_my_health; 2 - Social_expectations; 3 - PA_enough_stay_healthy; 4 - Intend_more_PA; 5 - Confident_more_PA; 6 - Concerned_current_PA; 7 - Important_more_PA

Self-efficacy for more PA (5) became less strongly (positively) connected to the intention to increase PA in the next two months (4) and perception of doing enough PA to be healthy (3). On the other hand, self-efficacy for more PA (5) became negatively connected to the concern for the current level of PA (6) and positively connected to the expectation that more PA would improve one's health (1) and the perceived importance of increasing their PA (7). This suggests that, through the course, the LP1 group became aware of relevance of PA for their health, so that the concern for their PA levels, the expectation that they could improve their health through PA and the importance of having more PA distinguished themselves as predictors of self-efficacy for more PA.

The correlation-stability (CS) coefficient for strength centrality for baseline (0.106) and follow-up (0.166) networks indicate low stability of this centrality measure in both networks. Therefore, we comment with caution on differences in the strength centrality between the two networks.

Figure 4 presents strength centrality values for all the items in both LP1 networks, whereas the exact values are reported in Section S3.1 of the Supplementary document. The concern for one's level of PA (6) kept its rather central position (2nd most central item). On the other hand, the intention to be more physically active in the next two months (4) and the perceived importance of increasing PA (7) became less central, whereas the expectation that more PA would improve one’s health (1) became the most central item.

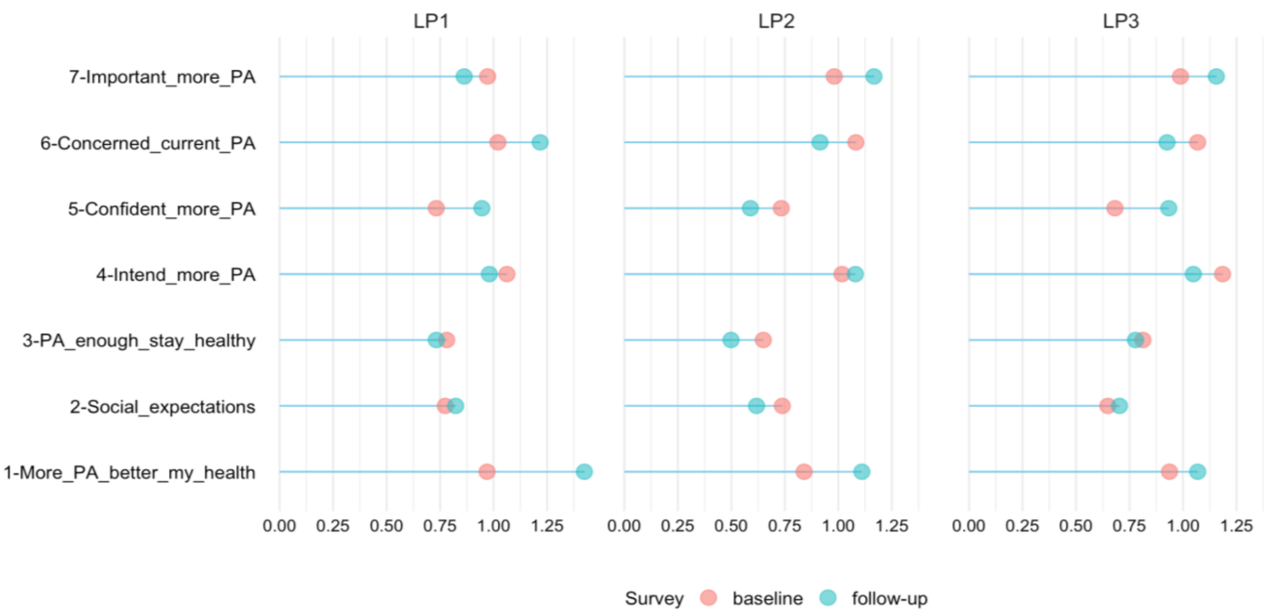


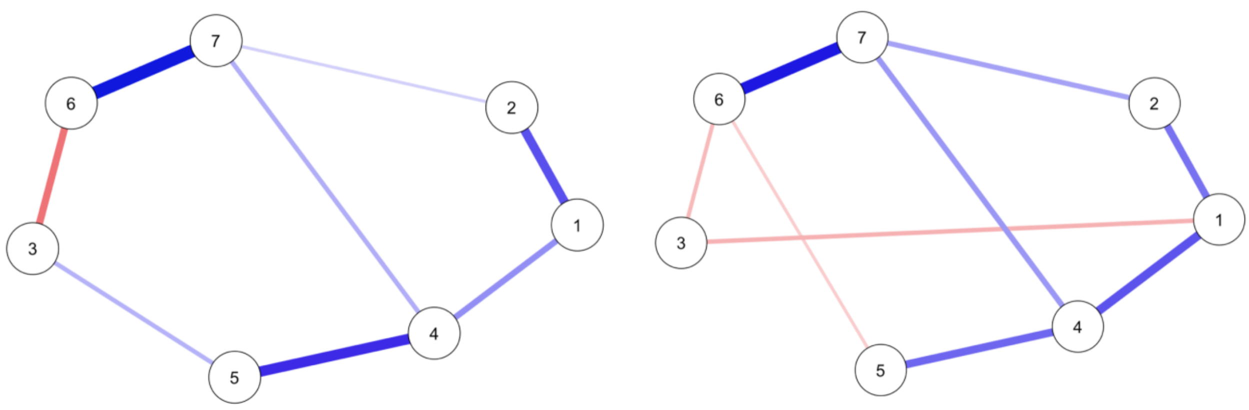
Figure 4. Strength centrality of items (nodes) in the baseline and follow-up networks for the three learner profiles

5.2.2 Learner profile 2

The Paired Wilcoxon Sign Rank test with Bonferroni correction applied to the baseline and follow-up responses of the participants in the LP2 group, identified significant differences for the same two survey items as in the case of LP1. Specifically, the perception of doing enough

PA to stay healthy increased (large effect size), whereas the concern for one's current level of PA decreased (medium effect size), as shown in Table 2[2].

The expectation that greater engagement in PA in the next two months would improve one's health (1) became more strongly (positively) connected to the intention to be more physically active in the next two months (4); at the same time, it became negatively connected to the perception of doing enough PA to stay healthy (3) and loosened its positive connection to the expectations for engaging in more PA by one's close social circle (2). In other words, how LP2 participants perceive the health benefits of increased PA became less affected by social expectations and at the same time more connected to how one perceives their current level of PA and their intention to increase PA.



(a) (b)

Figure 5. Networks estimated based on the responses of the LP2 group to the baseline (a) and the follow-up (b) survey. The correspondence between node labels and variables:
1 - More_PA_better_my_health; 2 - Social_expectations; 3 - PA_enough_stay_healthy; 4 - Intend_more_PA; 5 - Confident_more_PA; 6 - Concerned_current_PA; 7 - Important_more_PA

Figure 5 presents the estimated baseline (a) and follow-up (b) networks for the LP2 group. A comparison of the two networks provides the following information.

Next, the expectations for engaging in more PA by one's close social circle (2) became more strongly (positively) connected to the perceived importance of increasing one's PA (7). This

[2] The test results for all the survey items, including the descriptive statistics and effect size, are given in Section S6.2 of the Supplementary file.

suggests that while social expectations affect how the LP2 group perceived the relevance of more PA, this perceived relevance became less related to the direct benefits to one's health (as noted above) and more about general recognition of the benefits of being more PA.

Finally, the concern for the current level of PA (6) loosened its negative connection to the perception of doing enough PA to stay healthy (3), while becoming negatively connected to the self-efficacy for having more PA (5). This may suggest that the perception of one's level of PA was not as strong a source of concern as it was before the course, while at the same time the decrease in concern (Table 2) contributed towards higher self-efficacy for more PA (though the effect was not strong or long enough to result in statistically significant increase).

The correlation-stability coefficient for strength centrality for baseline (0.339) and follow-up (0.531) networks confirmed medium and high stability of the estimated centrality values ,in the two networks, respectively. Thus, we can safely examine differences in the strength centrality between the baseline and the follow-up networks (Figure 4)[3]. Specifically, the three most central items in the baseline network are *Concerned_current_PA* (6)*, Intend_more_PA* (4)*,* and *Important_more_PA* (7)*,* whereas the top-3 in the follow-up network are: *Importat_more_PA* (7)*, PA_enough_stay_healthy* (1), and *Intend_more_PA* (4). This suggests that the perceived importance of increasing PA (7) and the expectation that more PA would improve one's health (1) became the most central items, that is, the items with the highest ability to affect other PA-related items. On the other hand, the concern over one's level of PA (6) became less central, that is, with lower capacity to impact other PA-related items. In addition, the intention to be more physically active in the next two months (4) remained among the three most central items. .

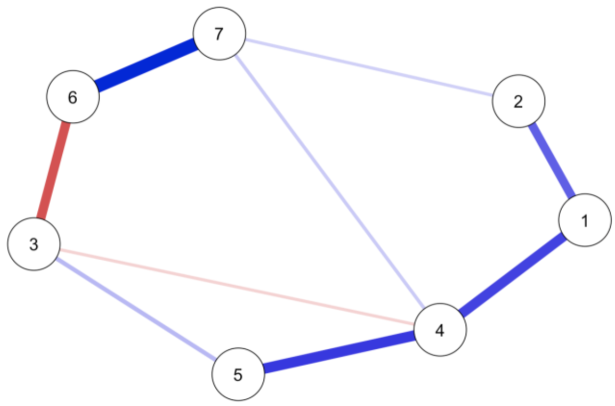
5.2.3 Learner profile 3

For the LP3 latent group, the Paired Wilcoxon Sign Rank test with Bonferroni correction identified three survey items as having significantly different responses to the follow-up survey compared to the baseline (Table 2)[4]. As in LP1 and LP2 profiles, the perception of doing enough PA to stay healthy increased while the concern for one's current level of PA

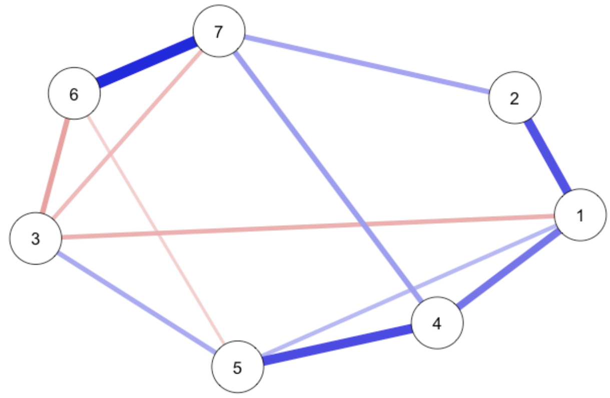
[3] The exact strength centrality values are reported in Section S3.1 of the Supplementary document.

[4] The descriptive statistics, estimated p-values, and effect sizes for all the survey items are given in Section S6.3 of the Supplementary document.

decreased. In addition, in LP3 only, we observe an increase in confidence that one would be more physically active in the next two months.



(a)



(b)

Figure 6. Networks estimated based on the responses of the LP3 group to the baseline (a) and the follow-up (b) survey. The correspondence between node labels and variables:
1 - More_PA_better_my_health; 2 - Social_expectations; 3 - PA_enough_stay_healthy; 4 - Intend_more_PA; 5 - Confident_more_PA; 6 - Concerned_current_PA; 7 - Important_more_PA

A comparison of the networks estimated based on the baseline (a) and follow-up (b) responses of the LP3 group (Figure 6) reveals the following.

The self-efficacy for engaging in more PA in the next two months (5) became negatively connected to the concern for one's current level of PA (6) and positively connected to the expectation that more PA would improve one's health (1). In other words, the concern about one's level of PA and their expectation that engaging in more PA in the next two months would improve their health have become predictive of the self-efficacy to engage in more PA in the next two months.

Next, the perception of doing enough PA to stay healthy (3) loosened its negative connection to the concern for one's current level of PA (6), while becoming negatively connected to the perceived importance of increasing one's PA (7) as well as the expectation that more PA would improve one's health (1). In other words, engagement with the course materials seems to have resulted in higher self-efficacy to increase PA levels in the next two months. The learners may have started applying some of the advice from the course and consequently potentially increased their PA levels. The more they thought/perceived they were doing enough PA, the more they were reassured that they were doing well for their health and that further increase in activity might not be needed, i.e. maintaining whatever level they achieved might be sufficient to maintain good health.

Finally, the intention to increase PA in the next two months (4) lost its negative connection to the perception of doing enough PA to stay healthy (3) and loosened its (positive) connection to the expectation that more PA would improve one's health (1). On the other hand, it became more strongly connected to the perceived importance of increasing PA (7), which, in turn, became more strongly connected to the expectations to be more physically active by one's close social circle (2). This suggests that the overall perceived relevance of increasing PA (directly) and social expectations (indirectly) became stronger predictors of one's intention to increase their PA in the next two months, while the perception of one's own level of PA and personal health benefits became less predictive of the intention for more PA.

Since the baseline and the follow-up network had, respectively, moderate (0.408) and low (0.219) stability of strength centrality, we examined and interpreted the differences in this centrality measure with caution. As for the other two profiles, strength centrality values for LP3 are presented in Figure 4, whereas the exact centrality values are reported in Section S3.1 of the Supplementary document.

The concern over one's level of PA (6) lost its highly central position. The intention to be more PA (4) lost its leading position in strength centrality, but remained among the top 3 most central items. On the other hand, the perceived importance of increasing PA (7) and the expectation that more PA would improve one's health (1) have become the most central items, that is, the items with the highest ability to affect other PA-related items.

6. Discussion

6.1 Discussion of the results

In response to our first research question (RQ1, Section 3), the study findings indicate that the proposed addition of psychological networks in the analysis of learners' self-reports collected before the start of the course offer more comprehensive information about the trace-based learner profiles, compared to the information offered by traditional statistical analysis only. In particular, the statistical tests revealed no difference among the three identified trace-based learner profiles in their PA-related perceptions, self-efficacy, and intentions (Section 5.1). On the other hand, network analysis of the same survey data revealed some valuable information about the trace-based learner profiles, which allows for a better understanding of their patterns of interaction with the course activities.

For example, unlike the other two profiles, LP1 seemed to be, at least partially, externally motivated to increase their level of PA, as social expectations were a predictor of both the group's perception of doing enough PA to be healthy and their intention to increase PA in the next two months. Furthermore, in LP1, the perceived importance of engaging in more PA was associated with the recognition of the health benefits of more PA, whereas for LP2 and LP3, it seemed to have a more active role, as it positively affected the intention to increase the level of PA in the next two months. These findings might, at least partially, explain why the LP1 group demonstrated a low level of activity during the course, more in the form of exploring the course materials than truly engaging with the course activities.

The network analysis also showed that LP3 differed from the other two profiles in that their intention to increase PA was 1) positively affected by the expectation that more PA would bring personal health benefits, and 2) negatively affected by the perception of doing enough PA to stay healthy. This may, to an extent, explain their strategic behaviour during the course, reflected in LP3 moderate level of activity, with roughly equal use of all tactics. Balanced use of tactics tends to indicate self-regulation of learning (Winne, 2013) and has been associated with higher course performance in MOOCs (e.g., Fan et al., 2021).

Related to our second research question (RQ2), the study results show that changes in the perceptions, self-efficacy, and intentions related to PA of each learner profile can be better understood if individual examination of the self-reporting survey items is complemented with an analysis of mutual connections of the same items. In particular, statistical tests applied to individual survey items and the network analysis of the same items offered complementary findings about the changes in the perceptions, self-efficacy, and intentions related to PA for each profile, as discussed below.

In the case of LP1 profile (low engaged, mostly browsing through diverse course resources), the course seems to have contributed to raising awareness of the health benefits of PA, since social expectations became less predictive of how those learners perceive PA, that is, the perceived relevance of PA became connected to one's own understanding of the health benefits of PA, instead of being dominated by the expectations of one's social circle. That learners with this profile, through the course, became aware of relevance of PA for their health is also suggested by the finding that the concern for PA, the expectation that one's health could be improved through PA, and the importance of having more PA became predictive of their self-efficacy for more PA. Furthermore, the expectation that more PA would improve one's health became the most central item, that is, the variable with the highest ability to affect other PA-related variables. Considering that this was the profile with the lowest level and quality of engagement with the course, these findings suggest that for those who have not yet internalised the relevance of PA for health, even a small "exposure" to good quality information can go a long way (Heath et al., 2012).

Learner profile LP2 gathers learners who were the most engaged with the course and very active in information gathering. For them, the expected health benefits of increased PA became more predictive of how they perceived their current level of PA and their intention to increase PA in the next two months. Furthermore, while social expectations remained predictive of how this group perceived the relevance of being more physically active, this perception became less related to the direct benefits to one's own health and more about general recognition of the health benefits stemming from being more physically active. Finally, the concern about one's level of PA became less affected by the perception of having enough PA for health, while at the same time becoming predictive of self-efficacy for more PA. That this group, on one hand, was the most active one in the course and, on the other, did not achieve more improvement than the least active group, might be explained by the level of physical activity and awareness of the relevance of PA that the two groups had when starting the course (analogous to the effect of prior knowledge in "regular" courses). In particular, it might be the case that the LP2 group gathered course participants who were already physically active and enthusiastic about PA and enrolled in this course to reassure themselves that what they were doing was beneficial for their health and/or to learn about additional ways to improve their PA. However, this is a conjecture that cannot be verified with the data used in the current study.

The LP3 group gathered the course participants who demonstrated a strategic approach to course activities (moderately engaged, committed to both information gathering and assessment). In this group, the concern about one's level of PA and their expectation that engagement in more PA would improve their health became predictive of the self-efficacy for increasing PA in the next two months. The joint effect of these two newly established connections plus the existing positive connection to the perception of doing enough PA to stay healthy might explain that only LP3 improved their self-efficacy to engage in more PA in the next two months. This improvement in self-efficacy might be (partially) attributed to

LP3's strategic approach to the course activities, as strategic use of learning tactics is often associated with positive course outcomes (Winne, 2013). Another finding for LP3 is that their perception of doing enough PA to stay healthy increased and become negatively associated with the perceived importance to increase one's level of PA and the expectation that more PA would improve one's health, suggesting that, through the course, these participants developed a kind of reassurance that they were already physically active enough to stay healthy and that maintaining the level they achieved may be sufficient and thus further increase of PA might not be necessary. This might be attributed to the LP3's engagement with the assessment activities in the course, in which this profile, compared to the other two, was the most active. Most of the assessments asked the participants to measure and report on their PA, which might have helped them become better aware of how they stand with respect to what is recommended for health benefits. Still, these effects were not strong enough to result in statistically significant change in the perceived importance of increasing PA levels and the expected health benefits of engaging in more PA. Finally, the intention to increase PA in the next two months became affected by the perceived relevance of increasing PA (directly) and social expectations (indirectly), while at the same time becoming less affected by the perception of one's own level of PA and personal health benefits. This seems to be in line with the above point that these participants became better aware of being physically active enough and thus the intention for more PA became primarily motivated by the general relevance of PA and how it has been framed in their social circle.

To conclude the discussion of the study results, we highlight that our findings provide sufficient evidence for a claim that learners' self-reports on their perceptions, intentions, and self-efficacy related to engagement in PA offer rich information for further description and better understanding of learner profiles derived from trace data. That is, self-reports offer complementary information to trace-based learning profiles, a finding that is fully in line with earlier studies that examined the correspondence and complementarity of learning trace data and self-reports (see Section 2.1). This study makes a step further by demonstrating how much more information can be derived from collected self-reports, if often used statistical methods - applied as the only method in prior related studies - are complemented with psychological networks as a means for studying relationships among measured items.

6.2 Limitations

Data availability and sample size are the key limiting factors of this study and the proposed use of psychological networks to examine mutual relations of survey items. The sample size limits the number of variables that can be examined through network analysis. In particular, if there are k variables, a partial correlation network of k nodes need to be estimated, that is, $k(k - 1)/2$ parameters (edges) need to be estimated (e.g., in our case, with 7 variables, 21 parameters were estimated for each network), and how well that estimation can be done depends on the sample size (Epskamp et al., 2018b). Similarly, how well centrality measures or other characteristics of the network structure can be estimated, is affected by the sample size. Sample size is also related to the statistical comparison of networks, which we had to skip due to the small size of individual learner profiles. Thus, we turned to descriptive network comparisons and to avoid overinterpretation, we opted for higher specificity (at the expense of sensitivity), which might have resulted in missing some true positives, that is, missing to identify some true connections between variables. Another limitation is that the presented analysis was performed in the context of one course only and a course that in its objectives differs from typical higher education courses, so, the study findings might not apply to more typical higher education courses. Furthermore, the current study needs to be replicated in learning contexts that differ from the examined one in terms of the learning design and course domain, as well as in terms of survey instruments used for measuring constructs of interest. Finally, as any analytics method that depends on self-reporting data collected through optional questionnaires, the proposed approach is prone to the self-selection bias since optional self-reporting surveys tend to be filled out by a subpopulation of learners who are better regulated and have better performance.

6.3 Implications

It is now well established that log data alone is not sufficient for understanding trace-based learner profiles or predicting learning outcome (Järvelä & Bannert, 2021; Jovanovic et al., 2021) and that students' self-reports are required for properly interpreting patterns in student learning behaviour (Fan et al., 2022b; Salehian Kia et al., 2021). Collection of self-reports for the purpose of better understanding learners' internal factors (e.g., perceptions, intentions, motivation) is associated with several challenges such as low response rates in case of traditional surveys or high attrition rates in case of longitudinal data collection. Considering the significant time and effort that researchers often put into collecting self-reports, it would be important to provide them with analytics methods that allow for distilling all potentially valuable information from the collected data. While not without limitations (outlined in the previous section), the analytic approach presented in this paper sets a path for a comprehensive analysis of self-reporting survey data and, consequently, developing better understanding of learners by combining insights derived from survey data with those obtained from learning traces.

We have demonstrated the proposed integrative analysis of trace and survey data in the context of a MOOC that is aimed at motivating and offering guidance for learners to engage in more PA while integrating it in their everyday life. The pre-post data collection scheme that was present in this course is in line with the objective of examining the effects of the course, as a form of educational intervention, on the participants' perceptions and attitudes to PA. If, on the other hand, the objective is to advise on the changes in the course design and content and/or the instructional support the participants would benefit from, it would be important to collect the participants' self-reports at multiple time points throughout the course. Such data could then be analysed through temporal networks, to explore the dynamics of distinct internal and / or external conditions and their mutual relations that characterise individual learner profiles, e.g., similar to (Fried et al., 2022). The relations in such temporal networks can be interpreted as Granger-causal, indicating how well one (internal or external) condition predicts other conditions at the next time point, after taking into account all other variables in the network (Epskamp et al., 2018a).

Furthermore, the approach presented in this paper contributes to network-based learning analytics, which has recently received increasing interest from learning analytics scholars (e.g., Shaffer, 2018; Swiecki & Shaffer, 2020; Chen & Poquet, 2022; Fan et al., 2022c). While each of the proposed approaches has some particularities, common to all of them is the recognition that networks are well fitted for analysing learning as an interplay of several interacting components, where those interactions and their temporal unfolding are at least as relevant as components themselves. The distinctive feature of our approach is that it combines individual item analysis (i.e., traditional statistical analysis) with analysis of item interconnections (i.e., network analysis), to glean comprehensive information from learners' self-reports. Furthermore, the obtained information about learners' internal states serves to complement information about patterns in learners' interactions with the course (i.e., learner profiles) derived from learning logs, which allows for a more thorough understanding of learners and their course engagement than any individual method or data source would allow for.

Last but not the least, the current study can inform the methods used for evaluating MOOCs, or similar digital educational interventions, aimed at promoting change in health-related behaviour. So far, the evaluation of health promoting MOOCs has been limited to simple statistical analysis (e.g., Adam et al., 2015; Perestelo-Perez et al., 2020; White et al., 2021; Tezier et al., 2022), offering just a basic level of understanding of the effectiveness of the delivered health interventions. Moving beyond MOOCs, a recent systematic review by Claflin et al. (2022) of online health educational interventions in the period 2010-2020 pointed to the need for more sophisticated methodological approaches to evaluating health educational interventions. In particular, Claflin et al. concluded that the evidence of the impact is scarce and pointed to the need for a better understanding of the profile of people that online interventions work for and the kinds of outcomes that can be achieved. The overall methodology applied in the current study - including the identification of trace-based learner profiles coupled with comprehensive analysis of self-reporting survey data - offers valuable guidance for bridging the gap identified by Claflin et al (2022).

Conflict of Interest statement:

The authors have no conflicts of interest to declare.

Data Availability Statement:

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Ethics statement:

The study was approved by The University of Edinburgh Moray House School of Education Ethics Sub-Committee.

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