Examining the Role of Academic Self-Efficacy on Achievement and Stress: A Network Analytic Approach

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Received: 26 May 2025 |
1st revision: 26 June 2025 |
2nd revision: 17 November 2025 |
Accepted: 19 November 2025

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APA citation for this article:
Ngamake, S. T., Raveepatarakul, J., Wisessathorn, M., & Kaewwongsa, S. (2025). Examining the role of academic self-efficacy on achievement and stress: A network analytic approach. *Journal of Institutional Research South East Asia, 23*(3), 142-175.

ABSTRACT

Academic self-efficacy has been found to have a consistent relationship with students' academic achievement and various psychological and educational outcomes. However, practitioners may encounter considerable challenges when designing interventions or support measures for students with diminished academic self-efficacy and suboptimal learning outcomes. One key difficulty arises from the broad scope of academic self-efficacy scales, which encompass a range of academic tasks and activities, both within and beyond the classroom, thereby complicating the identification of behavioral domains for intervention. As a consequence, much of the existing literature has focused on using more generic approaches such as stress reduction and cognitive reappraisal techniques to alleviate mental health concerns and enhance academic self-efficacy and achievement. In order to provide practitioners with more refined behavioral domains as a target for self-efficacy interventions, this study sought to identify efficacy beliefs critical to students' academic achievement and perceived stress, using various network analysis techniques. Data from 439 students were analyzed using psychological networks, network trees, and Bayesian networks. Through a triangulation of data analytic methods, results indicated that efficacy beliefs pertaining to managing time for study and schoolwork and using (associative) learning techniques were the most influential in strengthening efficacy beliefs in other academic domains, as well as in predicting academic achievement and stress. Developing and applying academic self-efficacy scales that explicitly capture learning techniques, coupled with designing self-efficacy interventions and guidelines tailored to a small number of critical behavioral domains, were proposed as practical implications.

Keywords: Academic self-efficacy, academic achievement, stress, network analysis, network trees, Bayesian networks, higher education

1. Introduction

The present study is motivated by the incongruence between a relatively well-established relationship between academic self-efficacy and academic outcomes, a theoretical framework regarding the sources of self-efficacy, and a way practitioners design interventions or guidelines aimed at enhancing students' academic self-efficacy to optimize their success. Meta-analytic studies have demonstrated the relationship between academic self-efficacy and various learning experiences and outcomes across both cross-sectional and longitudinal paradigms (e.g., Multon et al., 1991; Talsma et al., 2018). Thus, if practitioners seek to facilitate learning experiences and outcomes by reinforcing efficacy beliefs in various behavioral domains, they may consider leveraging the four sources of self-efficacy (Bandura, 1977) as foundational mechanisms. However, the breadth of behavioral domains within academic settings may be a challenge in developing a compact and targeted intervention for behavior change. Relying on research using a summative score of academic self-efficacy may obscure the selection of target behaviors. Worse still, different academic self-efficacy measures may contain item content that differs in dimensions and behaviors, rendering it more difficult to pinpoint behaviors most consequential for academic achievement. Hence, this study aimed to exploit the distinctiveness of item content in a measure assessing academic self-efficacy in predicting academic and mental health outcomes, using a network analytic approach. The resulting networks may be able to identify certain behavioral domains that are relatively more important than others, benefiting practitioners in creating more effective self-efficacy interventions/guidelines for university students. In addition, the findings may inform institutional-level strategies in higher education, potentially in developing university-wide policies and programs to enhance students' academic self-efficacy and, consequently, their academic achievement.

Self-efficacy has been defined as a person's expectation to successfully perform a designated behavior, especially in a challenging situation (Bandura, 1977). As a source of behavioral motivation, self-efficacy often determines which actions individuals will take, how much effort they will put in, and how long (or how many times) they will try when encountering obstacles. In the academic realm, self-efficacy across various endeavors has been found to play a pivotal role in shaping students' learning behaviors and academic outcomes (e.g., setting more challenging goals; Wood & Locke, 1987). Different aspects of psychological attributes subsumed under the label of "academic self-efficacy" have been proposed, which can be largely classified into two groups. The first group pertains to efficacy beliefs specific to academic subjects/courses such as mathematics, science, language, and so on (e.g., a belief in solving math problems; Matsui et al., 1990), and the second group pertains to efficacy beliefs regarding academic challenges within and beyond the classroom but not explicitly linked to any particular subjects/courses (e.g., a belief in taking notes or a belief in getting along with roommates; Gore et al., 2005; Zimmerman & Kitsantas, 2007). Although both groups have merit for different purposes and contexts, it seems that psychologists and educators may have trouble translating research into practice when empirical studies use academic self-efficacy measures that are not specific to any subjects/courses. This difficulty may arise from an inability to focus on a single or a small set of academic challenges when designing interventions.

Consider, for instance, the 19-item Self-Efficacy for Learning Form (SELF-A) developed by Zimmerman and Kitsantas (2007) and used in this study. A substantial body of research has observed that academic self-efficacy, as measured by the SELF-A, yielded a positive association with desirable outcomes and a negative association with undesirable outcomes (e.g., Mangus et al., 2021; Saroughi & Kitsantas, 2021). Given these findings, if psychologists and educators seek to design an intervention to enhance students' academic self-efficacy, they will be struck with varied item content embedded within this measure. Although the SELF-A has an established unidimensional factor structure, its item contents pertain to different academic tasks such as taking notes, preparing for the exam, or even motivating oneself. Of course, psychologists and educators may opt to cover all the academic tasks (as presented in the item content) in their intervention, but this practice may be overly time-consuming and resource-intensive for both practitioners and students, perhaps with a small margin of benefit when comparing to a more targeted intervention.

Alternatively, practitioners may resort to more generic techniques (i.e., not specifically tailored to the enhancement of academic self-efficacy; e.g., Perry et al., 2007). For example, employing an inquiry-based stress reduction approach to induce cognitive reappraisals in a quasi-randomized, control experiment, Krispenz et al. (2019) found that the intervention can increase academic self-efficacy and decrease test anxiety and academic procrastination among university students. With a three-wave data collection, the authors further found that academic self-efficacy can mediate the effect of the intervention on test anxiety but not academic procrastination. Furthermore, Bani et al. (2022) examined whether a cognitive-behavioral counseling intervention can alleviate psychological symptoms (e.g., anxiety and stress) and enhance academic self-efficacy among university students who self-enrolled in counseling services. Overall, the counseling intervention yielded desirable effects on psychological symptoms and academic self-efficacy, especially in a subgroup of students whose psychological symptom scores surpassed clinical thresholds. While these interventions have merit across a broad spectrum of academic and health-related outcomes, they were not designed specifically to boost academic self-efficacy. From a theoretical standpoint, these interventions were based largely on modulating emotional arousal (e.g., through a cognitive reappraisal of academic demands and/or personal resources to decrease stress levels), which has been found to be a less consistent source of self-efficacy (Byars-Winston et al. 2017). It may be unfortunate if self-efficacy interventions neglect performance accomplishments or vicarious experience (arguably more potent sources of self-efficacy) to facilitate behaviors of interest due to the overwhelming number of behaviors for practitioners to focus on. Hence, research that conducts an item-level analysis of academic self-efficacy is needed, with a suitable analytic approach that can extract useful information for designing a more targeted and effective intervention.

2. Literature review

Academic Self-Efficacy in Predicting Students' Outcomes

Self-efficacy has demonstrated a robust positive relationship with academic outcomes in various settings (e.g., elementary schools, high schools, or colleges/universities). A meta-analysis of 39 studies conducted by Multon et al. (1991) yielded a positive association of self-efficacy with academic outcomes ($r = .38$) such as academic tasks, classroom-related measures, and standardized tests. Self-efficacy also had a comparable effect size with measures of persistence-related metrics ($r = .34$) such as time on task, the number of tasks attempted/completed, and the number of academic terms completed. Further substantiating these findings, a study conducted by Robbins et al. (2004) classified psychological and study skill correlates into nine groups and meta-analyzed their associations with cumulative grade point average (GPAX) and academic retention. Academic self-efficacy yielded the largest effect size with GPAX ($r = .37$) and the second largest effect size with academic retention ($r = .24$). Similarly, Honicke and Broadbent (2016) meta-analyzed the relationship between academic self-efficacy and academic performance. Academic performance was conceptualized through several indicators, including GPAX, subject/course grades, exam scores, and credits obtained. They found that academic self-efficacy and academic performance had a moderate relationship when examined cross-sectionally (r = .33). Of note, several mediators and moderators have also been identified in the literature. Prominent mediators included goal-setting, effort regulation, metacognition, academic procrastination, academic self-discipline, deep processing, parental involvement, and conscientiousness, while prominent moderators included emotional intelligence, neuroticism, negative emotions, and time on task. More recently, Talsma et al. (2018) employed a meta-analytic cross-lagged panel analysis to examine the direction of the relationship between academic self-efficacy and academic performance. The results indicated a reciprocal effect between these two attributes, with the effect of academic performance on academic self-efficacy being larger than the reverse, signaling the importance of designing academic tasks that are moderately and incrementally challenging for learners. When further examining the specificity congruence hypothesis (i.e., domain-based versus task-based self-efficacy with task-based performance), the authors found that the cross-lagged effects were stronger in the case of specificity congruence (i.e., task-based self-efficacy and task-based performance), supporting the specificity congruence proposition of self-efficacy (e.g., Pajares & Miller, 1995). As self-efficacy has been theorized to be cultivated through four primary sources: performance accomplishments, vicarious experience, verbal persuasion, and emotional arousal (Bandura, 1977), Byars-Winston et al. (2017) meta-analyzed 61 studies that examined the relationship between these sources and academic self-efficacy. Using a model-based approach (i.e., a regression model), they found that these four sources collectively explained 28% of the variance in academic self-efficacy, with performance accomplishments being the strongest predictor (beta = .51).

Beyond its well-established association with academic performance, academic self-efficacy can have desirable effects on learning experiences and mental health outcomes. For example, more (academic) self-efficacious students reported more favorable learning experiences than less self-efficacious students (Bassi et al., 2007). That is, more self-efficacious students spent more time learning, experienced optimal states (i.e., a balance between challenges and skills) more frequently when performing academic tasks, and valued academic endeavors more strongly. Academic self-efficacy has been observed to positively associate with deep-processing learning strategies and negatively associate with surface-processing learning strategies, even when controlling for achievement goals (Fenollar et al., 2007). In addition to its impact on learning processes, academic self-efficacy has also demonstrated a negative relationship with mental health concerns, cross-sectionally and longitudinally. For instance, Zajacova et al. (2005) found negative, moderate-to-large correlation coefficients between (latent) academic self-efficacy and stress among first-year college students. Also within higher education settings, female and younger students were more likely to exhibit lower levels of academic self-efficacy and higher levels of stress than male and older students (Hitches et al., 2022). In high school settings, the inverse relationship between academic self-efficacy and stress was moderated by student gender, with the effect size being stronger in female students than in male students (Ye et al., 2018). Furthermore, a longitudinal study by Huang et al. (2023) demonstrated that academic self-efficacy mediated the effect of burnout over time. More interestingly, burnout levels of students themselves and their friends can predict changes in the students' academic self-efficacy and, in turn, predict their burnout levels in the next three months. Following Lambert and Newman (2023) and Tay and Jebb (2018), we would like to point out the property and the nature of the gradation of academic self-efficacy. In terms of its property, academic self-efficacy refers to individuals' beliefs in their capability to perform behaviors necessary for accomplishing academic tasks, and in terms of its gradation, it represents the varying strength of these beliefs. Based on self-efficacy theory and empirical evidence (e.g., Bandura et al., 1996), its primary function is motivational, encouraging students to engage and persist in academic tasks even in the face of obstacles. This motivating function, in turn, underlines a wide range of positive academic performance and mental health.

In terms of factors that potentially affect academic achievement in tertiary education (i.e., postsecondary, college, and undergraduate levels), academic self-efficacy has consistently demonstrated a positive relationship with several indicators of academic performance. A comprehensive review and meta-analysis conducted by Richardson et al. (2012) identified academic self-efficacy as one of three non-intellective psychological attributes that yielded a moderate effect size with GPAX (the other two were grade goal and effort regulation). The correlation coefficients were .36 among cross-sectional studies and .23 among longitudinal studies. A myriad of studies have also demonstrated the desirable impacts of academic self-efficacy in college and university settings. For example, Chemers and Garcia (2001) found that first-year students with high academic self-efficacy were likely to attain superior academic performance through perceiving academic tasks as challenging (rather than threatening) and maintaining high academic expectations. Also among first-year students, academic self-efficacy was positively related to time management and career commitment in cross-sectional analyses (although these relationships were not replicated in longitudinal analyses; Bargmann & Kauffeld, 2023). Moreover, medical students' academic self-efficacy displayed both direct and indirect effects on academic performance, with metacognitive learning strategies and positive affect (i.e., enjoyment, hope, and pride) serving as mediators (Hayat et al., 2020).

In the context of Thai higher education, academic self-efficacy has often been studied with academic procrastination. For example, in a study predicting academic procrastination among undergraduate students (Chatrakamollathas et al., 2022), self-efficacy for self-regulated learning had a negative relationship with academic procrastination, whereas academic self-efficacy (as defined by three dimensions–study, assignment, and social) had no relationship with academic procrastination (when controlling for other personal and contextual variables within a latent variable framework). Moreover, academic self-efficacy has been found to serve as a mediator for the relationship between achievement goal orientations and academic achievement, but this mediating effect was observed only among undergraduate students with passive procrastination, as opposed to those with active procrastination and non-procrastination (Ratsameemonthon et al., 2018). Self-efficacy has also been demonstrated to mediate the relationship between emotional intelligence and academic engagement among Thai undergraduate students (Villegas-Puyod et al., 2021). Despite these findings, an online CBT-based intervention was found to be effective in reducing academic procrastination but not in enhancing academic self-efficacy among undergraduate students (Doowa & Arikkatt, 2023). As previously noted, this lack of intervention effectiveness in increasing academic self-efficacy may be attributable to intervention designs that fail to target the sources of self-efficacy or specific behavioral domains central to academic functioning.

The Self-Efficacy for Learning Form

This study investigated the network structure of the SELF-A (Zimmerman & Kitsantas, 2007). Zimmerman and Kitsantas (2007) selected items for a short form of SELF, based on their content that primarily reflects a broad scope of studying and preparing for an exam, resulting in a unidimensional 19-item scale. In their validation study, hierarchical regression analyses revealed that the SELF-A scores significantly predicted college students' quality of homework completion and course grades, above and beyond their SAT scores (ΔR2 = .22 and .24, respectively). The SELF-A has been widely used to assess students' academic self-efficacy across the globe (e.g., Ahmad et al., 2024; Fenning & May, 2013; King-Sears & Strogilos, 2020; Mangus et al., 2021; Saroughi & Kitsantas, 2021; Stubbs & Maynard, 2017). For example, Fenning and May (2013) applied the SELF-A to freshman college students to examine whether academic self-efficacy can predict various academic and career-related outcomes. Stubbs and Maynard (2017) employed the SELF-A in a study comparing academic self-efficacy and school engagement among students with high, medium, and low levels of family cohesion and adaptability within a Caribbean sample. The item content in the SELF-A is congruent with the self-efficacy concepts originated by Bandura (1977). That is, the item content focuses on efficacy expectations but not outcome expectations. In his own words, efficacy expectations are "the conviction that one can successfully execute the behavior required to produce the outcomes" while outcome expectations are "a person's estimate that a given behavior will lead to certain outcomes" (Bandura, 1977, p. 193). All items contain the word "can" to signify a person's belief in his/her ability to carry out desired behaviors. Furthermore, in line with Bandura's (2006) recommendations, the item content was written based on specific academic tasks that are likely challenging for students, with a decile-based response format.

A Network Analysis

This study employed three techniques to explore the network structure underlying the SELF-A 19 items and their associations with two criterion variables: perceived stress and academic achievement. These techniques included network analysis (or psychological networks; Isvoranu et al., 2022), network trees (Jones et al., 2020), and Bayesian networks (e.g., Briganti et al., 2023). In essence, network analysis was initially conceptualized by Borsboom and colleagues (Borsboom, Cramer et al., 2011; Borsboom, Epskamp et al., 2011; Cramer et al., 2010) to study the intricate interrelationships among psychopathological symptoms. This technique has since gained attention from scholars and researchers across various fields such as personality psychology (e.g., Christensen et al., 2019) and organizational surveys (Letouche & Wille, 2022), to investigate the relationship between facets or items in psychological measures. The structure of the network (or network topology), as well as network parameters such as node centrality and the shortest path between nodes, is central to the analysis. Then, this technique has been integrated with model-based recursive partitioning (Jones et al., 2020) to explore whether variations in network parameters (e.g., partial correlations between nodes) can be reliably detected with respect to predefined splitting covariates (e.g., students' gender between male and female). Heterogeneity in network parameters results in the whole network being split into two subnetworks, with the splitting conducted hierarchically, starting with the most significant splitting covariate (the most differences in network parameters). Additionally, Bayesian network analysis (Scutari & Denis, 2015) has emerged as a technique for modeling probabilistic dependencies among nodes in the network. The gist of Bayesian network analysis is structure learning and parameter learning. Generally, the structure of the network can be algorithmically learned, the network parameters can then be estimated, and these processes can be derived from data, expert panels, and a combination of both. This study employed Bayesian network analysis, particularly for structure learning, to supplement potential probabilistic causal directions between nodes in the network (please see the Analyses section for further methodological details).

In the realm of academic self-efficacy, to our knowledge, there has been one study using network analysis techniques (Hu et al., 2024). Hu et al. (2024) examined the network structure and network parameters among perceived teacher autonomy support, academic self-efficacy, and learning engagement. Of particular note, the authors found that academic ability self-efficacy (one dimension of academic self-efficacy) and dedication (one dimension of learning engagement) functioned as bridge nodes, linking perceived teacher autonomy support to other dimensions of learning engagement. In other areas of studies, these network analysis techniques have been combined to explore the interconnections among items and variables. For example, Simonet and Castille (2020) used network analysis (Gaussian graphical models: GGM) and Bayesian networks (directed acyclical graphs: DAG) to investigate the relationship among personality aspects, job characteristics, experienced meaningfulness at work, and work behavior among working employees. The authors can identify the shortest paths from each personality aspect to meaningfulness, signifying potential mediators. Moreover, Bayesian networks can complement the results from network analysis by inferring probable directionality between the variable nodes, suggesting that meaningfulness may mediate the relationship between enthusiasm (one personality aspect) and several job characteristics. Budler and Stiglic (2023) applied network trees to examine potential covariates that may explain differences in the network parameters exhibiting the relationship between physical and mental well-being, parent relations, social support, and school environment among adolescents. A six-node network structure can be split based on an interaction between adolescents' age and gender, suggesting how to subset groups of adolescents when planning policies and interventions to improve their quality of life.

It is challenging to make an educated guess regarding the role of each SELF-A item in the network, as prior research has typically used the SELF-A as a unidimensional construct without examining specific items or subsets (Ahmad et al., 2024; Fenning & May, 2013; King-Sears & Strogilos, 2020; Mangus et al., 2021; Saroughi & Kitsantas, 2021; Stubbs & Maynard, 2017). As latent factors and network structures can, under certain conditions, be statistically equivalent (Van Bork et al., 2021), it is reasonable to infer that items showing strong factor loadings in previous studies may also emerge as central nodes in the network. Hence, drawing on the original validation study (Zimmerman & Kitsantas, 2007), four items with the highest factor loadings may be candidates for central positions in the network: Item 2 ("summarize complex lecture notes"), Item 7 ("associate new concepts with old ones"), Item 12 ("change other priorities to have enough time for studying"), and Item 14 ("motivate oneself for a disliked subject"). Moreover, even though the SELF-A has been treated as unidimensional, an inspection of its item content may suggest a potential for grouping. Five conceptual groups can be proposed based on the behavioral focus of the items: cognitive and meta-cognitive strategies (e.g., summarize complex lecture notes), motivational and self-regulatory control (e.g., motivate oneself for a disliked subject), social management (e.g., find another student to explain the lecture notes), priority and time management (e.g., change other priorities to have enough time for studying), and evaluative and reflective learning (e.g., go back to notes and locate the forgotten information). A meta-analytic study examining non-intellective correlates of academic achievement found that effort regulation played a substantial role (Richardson et al., 2012), highlighting its importance as a modifiable self-regulatory process that has consistently predicted university students' GPAX above and beyond prior performance and cognitive ability. Therefore, it can be proposed that the items reflecting motivational and self-regulatory control (i.e., Items 3, 9, 10, 14, and 15) may potentially exhibit a distinct relationship with academic achievement in the network. If this educated guess holds, educators should focus on fostering students' efficacious beliefs through performance accomplishment strategies, such as providing structured, step-by-step opportunities for students to gradually learn and integrate these motivational and self-regulatory skills into their academic routines.

Accordingly, this study aimed to investigate the network structure of the SELF-A, with and without two criterion variables, to address these research questions:

1. Which domain(s) of academic self-efficacy exert the greatest influence within the SELF-A network? This question is addressed through the interpretation of network centrality indices from network analysis (without the criterion variables).
2. Which domain(s) of academic self-efficacy exhibit the shortest path to the criterion variables, and what is the likely direction of these associations (i.e., from specific SELF-A items to the criterion variables or vice versa)? This question is addressed through the interpretation of bootstrapped partial correlations and shortest path lengths from network analysis, and directional inferences from Bayesian network analysis.
3. Does the structure of the SELF-A network differ as a function of certain covariates (i.e., students' gender, years of study, and an averaged score of the SELF-A)? This question is addressed through split netwok models from network tree analysis.

Answering these research questions will hold significant implications for psychologists, educators, and practitioners regarding policies and interventions that tackle academic tasks or activities perceived by students as particularly challenging (i.e., low self-efficacy). This study offered a different viewpoint from the study by Hu et al. (2024) in that it emphasized an item-level analysis with two important outcomes in college/university life. From an applied perspective, identifying the behavioral domains wherein efficacy beliefs play a significant role in predicting academic and mental health outcomes will be informative for practitioners to design focused interventions and guidelines aiming at these critical aspects of academic endeavors. Figure 1 displays the research framework with the operationalization of the focal variables. Notably, lines rather than directional arrows were used to depict associations, in order to reflect the study's neutral stance on directionality prior to conducting Bayesian network analysis.

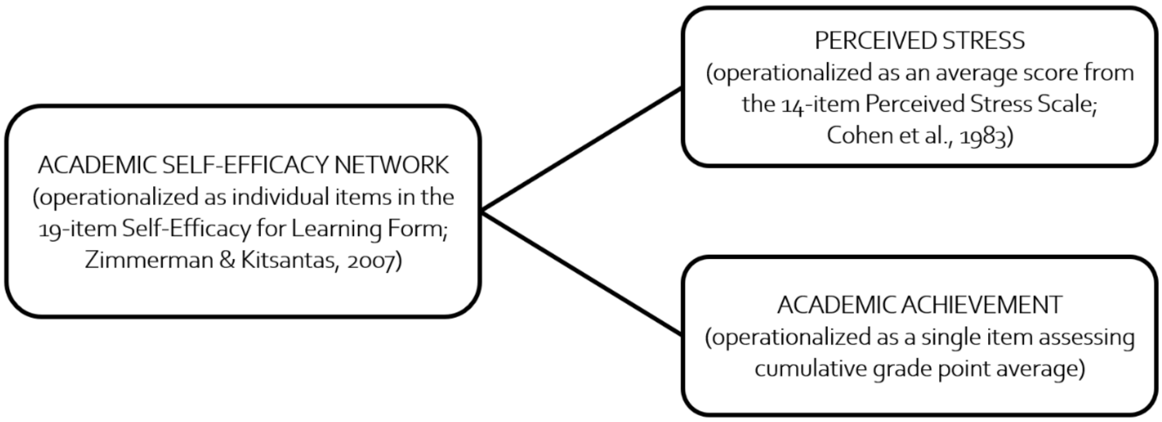

Figure 1: The Research Framework

3. Methods

Procedures and Participants

Utilizing a secondary data analysis approach, this study used a subset of data from the work of Ngamake et al. (2013). With ethical approval granted by the university of the third author in the original study, the original study collected four-wave data, with a two-week interval between the second and eighth weeks of the spring (second) semester, from undergraduate students enrolled in various departments and programs at a large university in Thailand. Students reported demographic information and four psychological predictors (i.e., academic coping strategies, academic self-efficacy, self-regulation, and achievement goals) during the first wave and reported their stress levels across all four waves. Of the 439 students who participated in the first wave, only 198 students (45.1%) completed all four waves, and the original report used data exclusively from this longitudinal subset. For the present study, the data from the first wave ($N = 439$) were used, with GPAX, academic self-efficacy, and stress as the focal points of the investigation. This data set has not been used in any prior research. Interested readers who would like to access the data set may contact the first author, who can provide it upon reasonable request. The participants comprised 96 male (21.9%), 335 female (76.3%), and 8 transgendered (1.8%) students, with an average age of 20.4 years ($SD = 2.5$ years). The majority were first-year students ($n = 144$; 32.8%) and the breakdown of the GPAX was as follows: 144 students (26.0%) attained a GPAX between 3.60 and 4.00, 136 (31.0%) between 3.20 and 3.59, 115 (26.2%) between 2.80 and 3.19, 52 (11.8%) between 2.40 and 2.79, and 22 (5.0%) below 2.40.

Measures

This study's measures comprised four items and two psychological scales. Three demographic items captured participants' sex, age, and years of study. As a proxy of academic achievement, a single item assessed participants' GPAX using an ordinal response format with five categories: below 2.40, 2.40-2.79, 2.80-3.19, 3.20-3.59, and 3.60-4.00. The two psychological measures were the SELF-A (Zimmerman & Kitsantas, 2007) and the Perceived Stress Scale (PSS; Cohen et al., 1983). Both measures were translated into Thai and subsequently back-translated to ensure semantic equivalence with the original versions.

The Self-efficacy for Learning Form

The SELF-A (Zimmerman & Kitsantas, 2007) contains 19 items measuring students' academic self-efficacy with an emphasis on self-regulated learning. Item examples are "When you miss a class, can you find another student who can explain the lecture notes as clearly as your teacher did?" and "When you find that you had to 'cram' at the last minute for a test, can you begin your test preparation much earlier so you won't need to cram the next time?" We modified the response format from 0-100 with 10-point increments to 0-10 with 1-point increments for practical purposes. Higher scores on the SELF-A indicated greater levels of academic self-efficacy. From its validation study, the SELF-A scores yielded a well-fitting unidimensional factor structure, along with an excellent internal consistency reliability (alpha = .97). Although the summative score of the SELF-A was not central to the present study, the SELF-A scores in the current sample exhibited good internal consistency reliability, with an alpha coefficient of .93 and an omega coefficient of .93. The list of the 19 SELF-A items is provided in Table A1 in the Appendix. To examine whether the SELF-A maintained its unidimensional structure, we conducted a parallel analysis and a confirmatory factor analysis (CFA). The result of the parallel analysis indicated that only the first factor's eigenvalue exceeded the corresponding eigenvalue derived from simulated and resampled datasets, supporting a single-factor solution. Specifically, the first factor's eigenvalue (8.84) was approximately 8.5 times larger than the second factor's eigenvalue (1.04). Moreover, even though the CFA indicated a mediocre fit (chi-square[152, $N = 439$] = 441.3, $p < .05$, CFI = .926, RMSEA = .066, and SRMR = .042), an inspection of the residual correlation matrix showed that the sources of misfit were scattered rather than concentrated within specific item clusters. Only 4 out of 171 residual correlations had absolute values greater than .10, suggesting that the sources of misfit could not be located exactly and that the SELF-A was unlikely to possess a multidimensional structure. Of note, all factor loadings were statistically significant, with standardized estimates ranging from .47 to .74.

The Perceived Stress Scale

The PSS (Cohen et al., 1983) contains 14 items (with 7 items reverse-scored) asking respondents to indicate the extent to which they have experienced stress-related feelings and thoughts over the past two weeks. Item examples are "In the last two weeks, how often have you been upset because of something that happened unexpectedly?" and "In the last two weeks, how often have you dealt successfully with irritating life hassles?" (reverse-scored). The response format was 0 = never, 1 = almost never, 2 = sometimes, 3 = fairly often, and 4 = very often. A composite score was derived by averaging all item responses, accounting for the reverse-scored items, with higher scores denoting greater stress levels. In its original study, the PSS scores had good internal consistency reliability (alphas ranging from .84 to .86 across three independent samples) and had positive associations with the number of life events and the severity of physical symptoms experienced (Cohen et al., 1983). In the context of this study, the PSS scores demonstrated adequate internal consistency reliability, with an alpha coefficient of .71 and an omega coefficient of .73.

Analyses

As there was a small amount of item-level missing data on academic self-efficacy and perceived stress (less than 1%), the expectation-maximization algorithm was used for missing data imputation (Graham, 2009), using the Amelia package within the R environment (Honaker et al., 2011). There were no missing data on academic achievement (operationally assessed via a single-item GPAX) or other demographic variables, except for years of study (e.g., freshman, sophomore, and so on). Therefore, three students who did not report their years of study were excluded from the network tree analysis, where this variable served as a splitting covariate.

Psychological networks were constructed to investigate the structural interrelations among the SELF-A 19 items, with and without criterion variables (perceived stress and academic achievement). For the network without the criterion variables, the primary objective was to identify the most influential item(s), using closeness centrality and expected influence indices. For the network with the criterion variables, the primary objective was to identify the item(s) that have a direct relationship with each criterion, as well as to locate the shortest paths from certain items (i.e., those with the lowest means) to these criteria. Because GPAX comprised five ordered categories, it was treated as an ordinal variable. Accordingly, we computed polychoric correlations between GPAX and the other nodes in the network to obtain a more accurate estimation of associations. We adhered closely to the reporting standards for psychological networks recommended by Burger et al. (2023). The psychological networks were estimated using the ggmModSelect method with a stepwise procedure in the qgraph package (Epskamp et al., 2012). Essentially, the ggmModSelect method estimates a series of networks with varying degrees of regularization (i.e., reducing model complexity by shrinking network edges, with some weak edges being shrunk to exactly zero). Once the edges fixed at zero were determined, each network was then reestimated as partial correlations without regularization, and the network with the lowest Bayesian Information Criterion (BIC) was selected and then refined by adding and subtracting edges in a stepwise fashion until the optimal BIC was obtained. Simulation studies have demonstrated that the ggmModSelect method performed well, especially for centrality estimation and network replicability (Isvoranu &

Epskamp, 2023). For visualization, the network layout was constructed using the Fruchterman-Reingold algorithm , which is a default option in the qgraph package.

Two centrality indices, closeness centrality and expected influence, were emphasized in this study. The closeness centrality signifies the influence of a node on other nodes within a network, such that a change in a node with a high closeness centrality will rapidly spread its impact throughout the entire network. Originally developed for use in mental disorder networks, the expected influence signifies the influence of a node on its local nodes, taking the direction (i.e., positive and negative) of an edge into account, with an aim "to assess the nature and strength of a node's cumulative influence within the network" (Robinaugh et al., 2016, p. 748). There are two types of expected influence: one-step expected influence and two-step expected influence. One-step expected influence captures a node's influence on its immediate neighbors, while two-step expected influence captures a node's influence on its immediate neighbors and their subsequent connections. This study considered both types of expected influence, with closeness centrality computed via the qgraph package (Epskamp et al., 2012) and the two types of expected influence computed via the networktools package (Jones, 2024). To gauge the stability of the centrality indices and the variability of parameter estimates, we employed a bootstrapping technique. That is, a set of 1,000 bootstrapped samples with a decreasing proportion of sample sizes was generated to investigate the stability of the centrality indices (Epskamp et al., 2018) and a separate set of 1,000 bootstrapped samples was generated to calculate a split-0 bootstrapped confidence interval (split-0 BCI; Fried et al., 2022). This bootstrapping technique was implemented via the bootnet package (Epskamp et al., 2018), and more technical details about each bootstrapped sample set were described in the Results section.

To further explore the differences in network structures, we conducted a network tree analysis with an 8-item version of the SELF-A (along with the two criterion variables) as nodes and students' gender, years of study, and an averaged score of the SELF-A as potential splitting covariates. Due to the limited number of students who self-identified as transgendered or were in their fifth year of study, the network trees were analyzed with only male and female students, and the fourth- and fifth-year students were combined into a single category ($n = 431$). These eight items were selected to optimize large-scale screening, using an ant colony optimization algorithm (Leite et al., 2008) to retain items with high factor loadings, as well as measurement invariance across genders (for factor loadings and intercepts), while simultaneously their latent factor had strong predictive utility in relation to these two criterion variables. Using the networktree package (Jones et al., 2020), a partial correlation network was constructed with a model-based recursive partitioning algorithm applied for network splitting. Unfortunately, the networktree function does not currently support polychoric correlations as input data. However, this limitation was unlikely to have a substantial impact on the results, as the discrepancy between Pearson and polychoric correlation coefficients was negligible (averaging only .005, with the largest difference being only .009). The goodness-of-fit measure was computed for split samples, and the splitting covariate and its cut point that yielded the most improved goodness-of-fit measure (returning the smallest p-value) were selected. The splitting process was halted when no further split resulted in a significant improvement in the goodness-of-fit measure.

For the Bayesian network analysis, we focused on structure learning to identify directed relationships between nodes, based on a joint probability distribution among variables (Scutari, 2010). The structure of Bayesian networks relies on the concept of d-separation (Pearl et al., 2016), which asserts that two nodes are statistically independent when controlling for their common causes and intervening variables but not for their common effects (Hayduk et al., 2003). Hence, in Bayesian networks, if two nodes do not have a directed edge connecting them (in other words, they are "d-separated"), they are either independent or conditionally independent when controlling for other nodes. In contrast, if two nodes have a directed edge, they are dependent; that is, a causal relationship can be statistically assumed but cannot be firmly ascertained, as Bayesian networks identify only admissible or probabilistically inferred causal pathways rather than verified causal mechanisms (interested readers may refer to Briganti et al. [2023] and Darwiche [2010] for further explanation on how directed edges in Bayesian networks can be interpreted as probabilistic inferences of causal relationship within cross-sectional data).

We used the bnlearn package (Scutari, 2010; Scutari & Denis, 2015) for Bayesian network analysis. To confidently identify directed edges within Bayesian networks, a bootstrapping technique (Friedman et al., 2013) was combined with a hill-climbing algorithm (HC). In particular, a certain number of bootstrapped samples (1,000 in this study) were drawn with replacements from the original sample. Data from each bootstrapped sample were subject to the HC to derive a network structure. As a score-based structure learning algorithm, the HC begins with an initial network (typically devoid of edges) and then adds or subtracts an edge, or reverses its direction, one edge at a time, and computes a network score (usually BIC) that reflects the goodness-of-fit between the structure of the network and the dependency of the data (partial correlation in the case of this study, where Gaussian Bayesian network was estimated; Briganti et al., 2023; McNally, 2016). When the network score can no longer be improved, the algorithm returns the final network. However, the HC usually suffers from local dependence, where the resulting network may not have the highest score possible (i.e., local maxima rather than global maxima). This problem can typically be overcome through a restarting process with randomly added/subtracted/reversed edges, but for this study, the bootstrapping technique was used to address the local maxima problem instead. The resulting networks from each bootstrapped sample were averaged to generate a stable network structure. Researchers may set a criterion for retaining edges in the network to get a more robust network structure (McNally, 2016). For this study, an edge that appeared in more than 80% of the bootstrapped samples was retained. A simulation study of the bootstrapping method (Friedman et al., 2013) found that this method is quite conservative in that bootstrapped samples contain a small number of false positive edges, and this number is usually smaller than that of false negative and true positive edges. That is, when there is no relationship between nodes in the "true" network, the bootstrapped networks are less likely to produce a spurious relationship, rendering increased confidence in the detected edges.

The focus of the Bayesian network in this study was on learned network structures, rather than learned parameters. Specifically, our interest lay in examining whether the network structure derived from the Bayesian network corresponded to that derived from the network analysis, rather than in estimating parameters or predicting the magnitude of the criterion variables. Hence, we opted to retain the Gaussian Bayesian network, as opposed to a hybrid Bayesian network (which combines discrete and continuous variables), despite the fact that GPAX was measured on a five-point ordinal scale. This approach has been supported by several lines of evidence: (a) the observed distribution of GPAX did not substantially deviate from normality (skewness = -0.49 and kurtosis = -0.54); (b) as noted earlier, the Pearson correlation coefficients between GPAX and the other variables were comparable to their corresponding polychoric correlation coefficients; and (c) a simulation study (Zhu & Nguyen, 2024) demonstrated that, for network structure learning, treating all variables as continuous and estimating a Gaussian Bayesian network yielded a reliable network configuration. Specifically, Zhu and Nguyen (2024) introduced a "Run it As Gaussian" strategy to estimate a Gaussian Bayesian network while treating a mixture of continuous and ordinal variables as if they were all continuous. They found that this strategy performed comparably to computationally intensive methods that model the joint distribution of continuous and ordinal variables and outperformed methods that discretize continuous variables (which can lead to information loss).

4. Results

Data from the SELF-A and the two criterion variables were subjected to descriptive analysis. On a scale ranging from 0 to 10, the SELF-A items had averaged scores ranging from 6.17 (Item 3 "motivate oneself to keep good notes from a boring lecture") to 7.65 (Item 9 "keep up with assignments despite having problems with friends and peers"), implying the most and least challenging tasks, respectively. The score distributions from all items were approximately normal, with skewness ranging from -0.67 to -0.23. Inter-item correlation coefficients varied between .25 and .61 with an average inter-item correlation of .43. At the scale level, academic self-efficacy had a mean of 7.13 ($SD = 1.42$), and perceived stress had a mean of 1.73 ($SD = 0.42$) on a response scale from 0 to 4. Academic self-efficacy yielded a negative relationship with perceived stress ($r = -.30$, $p < .01$) and a positive relationship with academic achievement ($r = .17$, $p < .01$). Perceived stress was not related to academic achievement ($r = -.07$, $p = .13$), however.

Network Analysis

Partial correlation data from the SELF-A items were subjected to psychological network analysis. As depicted in Figure 2, all the edges in the network demonstrated a positive relationship, supporting the internal structure of the measure. Given that Item 3 had the lowest mean, signifying a very challenging task in the academic realm, identifying other nodes that have a strong connection to this item may be valuable in helping students cope with this academic demand. The four items with the shortest paths to Item 3 were Items 2, 4, 10, and 14, demonstrating the importance of making notes and summaries from lectures (Items 2 and 4), attention and concentration (Item 10), and self-motivation (Item 14). Moreover, when examining the centrality indices (i.e., closeness centrality and expected influence), two items stood out. Illustratively, Item 12 ("change other priorities to have enough time for studying") had the highest closeness centrality and ranked second and third in one-step and two-step expected influence, respectively. Also, Item 17 ("find a way to associate technical details of a concept together that will ensure recall") had the highest one-step and two-step expected influence and ranked second in closeness centrality. To further examine the stability of node centrality (i.e., closeness and one-step expected influence), we bootstrapped 1,000 samples with decreasing sample sizes from 5% to 60% (in 5% increments) and tested for the maximum proportion of sample size that could be dropped such that the 95% confidence interval of the relationship between the original centrality indices and those computed from the resampled subsets remained above .70 (for "stable" node centrality, the proportion of the sample sizes dropped should be at least 25%; Epskamp et al., 2018). We found that closeness centrality was not stable (the proportion of sample size that could be dropped was less than 5%), while one-step expected influence was stable (the proportion of sample size that could be dropped was around 45%). Despite the instability in closeness centrality at the global level, an inspection of node-wise closeness centrality from bootstrapped samples showed that Items 12, 14, 17, and 18 consistently exhibited higher closeness centrality than the other items, even though the ranking of these items fluctuated across resampled subsets (see the Appendix for a supplementary table presenting the closeness centrality and expected influence of each item, along with three supplementary figures displaying the stability of node-wise closeness centrality and expected influence across the resampled subsets).

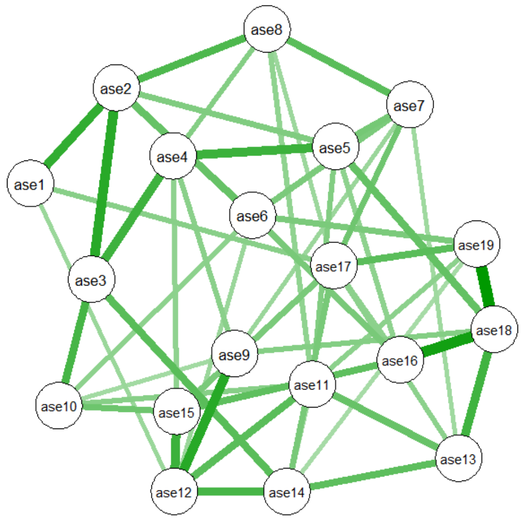

Figure 2: A 19-item ggmModSelect Network
Note: N = 439; EBIC tuning parameter (gamma) = 0, leading to BIC model selection.

Next, two criterion variables (i.e., perceived stress and academic achievement) were included in the network. A ggmModSelect network indicated that Item 4 "clarify the confusion of the instructor's lecture" and Item 7 "associate new concepts with old ones" had a direct, negative relationship with perceived stress, and only the latter had a direct, positive relationship with academic achievement (Figure 3). For parameter estimation (i.e., partial correlation), we generated 1,000 bootstrapped samples in order to calculate a split-0 BCI. According to Fried et al. (2022), a split-0 BCI contains two pieces of information: (a) a 95%BCI computed only from bootstrapped samples with a non-zero parameter estimate; and (b) the proportion of the bootstrapped samples with a non-zero parameter estimate. This split-0 BCI is suitable for the ggmModSelect method, where certain edges were fixed (as opposed to regularized) as zero. However, Fried et al. (2022, p. 136) have warned that this split-0 BCI should be interpreted merely as "variability in parameter estimates that is to be expected in the data", rather than in the same way as a typical confidence interval (CI) such that it contains the true parameter value with a predetermined probability (e.g., 95%). As a result of the bootstrapped samples, a negative partial correlation between Item 4 and perceived stress was observed (parameter estimate = -.13 and 95% split-0 BCI = [-.21, -.10] with 48.9% of bootstrapped samples having a non-zero coefficient). Item 7 also demonstrated a negative partial correlation with perceived stress (parameter estimate = -.17 and 95% split-0 BCI = [-.23, -.10] with 83.4% of bootstrapped samples having a non-zero coefficient) while showing a positive partial correlation with academic achievement (parameter estimate = .13 and 95% split-0 BCI = [.09, .20] with 44.5% of bootstrapped samples having a non-zero coefficient). Furthermore, when examining shortest path lengths between nodes, Item 7 had the shortest path to both perceived stress (shortest path length = 5.65) and academic achievement (shortest path length = 7.25) while Item 4 had the next shortest path to perceived stress (shortest path length = 7.33). Moreover, when focusing on the items with relatively low descriptive means (i.e., below 7.0; Items 2, 3, 10, and 14) and their connections to the criterion variables, we found that the shortest paths involved only a few intermediary items (Figure 4). The relationship between Items 3 and 4 seemed to serve as a bridging edge, linking Items 2, 10, and 14 to perceived stress. For academic achievement, Items 6, 8, and 17 seemed to connect the items with relatively low descriptive means to Item 7 and then advance to academic achievement. This outcome may highlight the roles of learning techniques to summarize and integrate course content into a coherent whole (Items 6 and 17) and studying with peers/classmates (Item 8) on students' academic achievement.

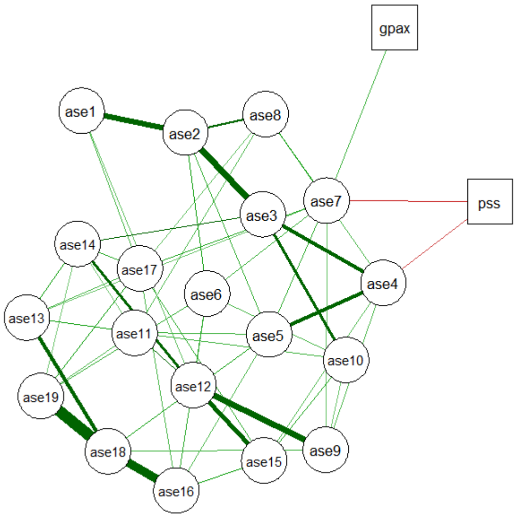

Figure 3: A ggmModSelect Network with the Criterion Variables

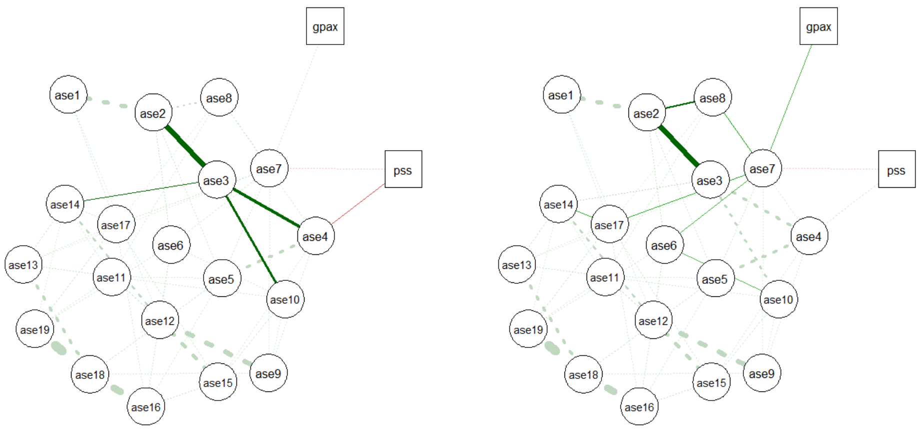

Figure 4: Shortest Paths from Items 2, 3, 10, and 14 to Perceived Stress (Left) and Academic Achievement (Right)

Network Trees

To begin with, the 8-item SELF-A network was analyzed. We found that students' gender was the only significant splitting covariate ($p = .035$). Figure 5 displays juxtaposed networks (left) and a contrasted network (right). With eyeballing, the male network appeared denser and contained some negative relationships between nodes, which were absent in the female network. An inspection of node centrality revealed that, for the male network, Item 18 "go back to notes and locate the forgotten information" had the highest closeness centrality, and Item 12 "change other priorities to have enough time for studying" had the highest one-step expected influence. For the female network, Item 14 "motivate oneself for a disliked subject" had the highest closeness centrality as well as the highest expected influence. When contrasting a set of partial correlations between the two networks, we can classify the most different edges into three groups. The first group contained the edges between Items 3 and 18 and between Items 13 and 16, where male students yielded a positive relationship while female students yielded a null relationship (partial correlation coefficients with an absolute value less than .10). The second group contained the edges between Items 6 and 16, between Items 13 and 14, and between Items 16 and 17, where female students had a positive relationship, while male students had a null relationship. The third group contained the edges between Items 3 and 13 and between Items 14 and 18, where male students exhibited a negative relationship while female students exhibited a null relationship. Upon incorporating the two criterion variables (i.e., perceived stress and academic achievement) into the 8-item SELF-A network, no splitting covariates yielded a significant result (with the total score of SELF-A yielding the smallest p-value of .11).

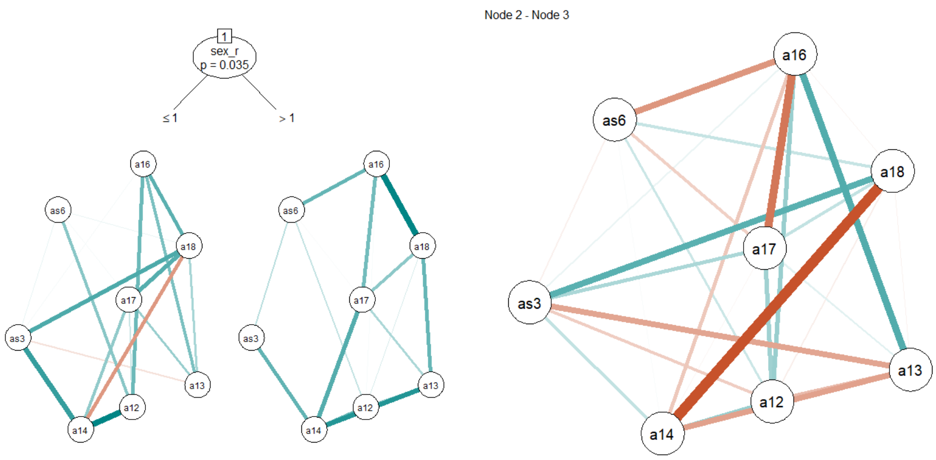

Figure 5: The 8-item SELF-A Network Tree

Note: n = 431; partial correlations with only an absolute value of at least .10 were shown. "≤ 1" was the male group, and "> 1" was the female group. As a further note, we also estimated a network tree that included all 19 items of the SELF-A. The resulting networks (both with and without the criterion variables) showed comparable structures, and no statistically significant splits were detected based on the splitting covariates.

A Bayesian Network

To further examine the directionality of the relationship between the SELF-A items and the two criterion variables, a Bayesian network was constructed. No a priori constraints were imposed on the role of the nodes. More specifically, we did not inhibit (or "blacklist") the direction from the two criterion variables to the SELF-A items, allowing for the possibility that perceived stress and/or academic achievement might statistically impact academic self-efficacy. One thousand bootstrapped samples were generated, and structure learning was performed for each sample using the HC. The bootstrapped networks were averaged to create a more robust network structure, in which only edges surpassing a predefined threshold were realized. Applying a threshold of .80 (edges that appeared in at least 800 bootstrapped samples), Figure 6 displays the averaged network, where the thickness of the edges conveyed the degree of confidence in the relationships between nodes (the thicker the edge, the higher the confidence). Four impressions can be discerned from the Bayesian network: (a) Item 7 had a relationship with perceived stress, with the direction more likely flowing from the former to the latter rather than vice versa (i.e., directed probabilistic dependencies; McNally, 2016); (b) academic achievement had no association with any items; (c) two items (Items 12 and 18) were root nodes, serving as common antecedents to many items; and (d) four items (Items 1, 9, 10, and 13) were terminal nodes. To facilitate understanding and provide a clearer overview of the findings, Table 1 presents a summary linking the research questions, methodological approaches, and key findings with their corresponding implications.

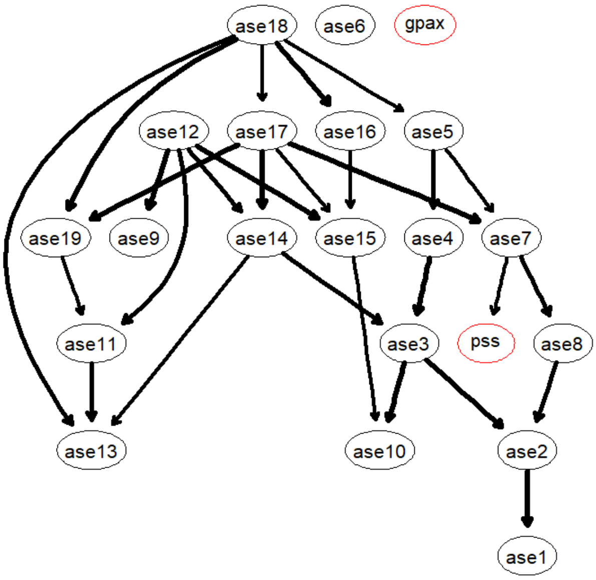

Figure 6: An Averaged Bayesian Network with Threshold = .80
Note: gapx represented academic achievement, and pss represented perceived stress.

Table 1: A Summary of Research Questions, Methodological Approaches, and Research Findings and Implications

Research Questions	**Methodological Approaches**	**Key Findings and Implications**
1. Which domain(s) of academic self-efficacy exert the greatest influence within the SELF-A network?	Network analysis with centrality indices	Item 12 ("change other priorities to have enough time for studying") and Item 17 ("find a way to associate technical details of a concept together that will ensure recall") emerged as the most influential nodes. Increasing efficacy beliefs in these domains may effectively strengthen efficacy beliefs in the other domains (the other nodes).
2. Which domain(s) of academic self-efficacy exhibit the shortest path to the criterion variables, and what is the likely direction of these associations?	Network analysis with bootstrapped partial correlations and shortest path lengths, and a Bayesian network with a directed relationship	Item 7 ("associate new concepts with old ones") consistently demonstrated a statistical impact on perceived stress. Increasing efficacy beliefs in this domain, as well as related learning skills, may serve as a protective factor against academic stress.

3. Does the structure of the SELF-A network differ as a function of certain covariates?	Network trees (a combination of network analysis with model-based recursive partitioning)	Only the 8-item SELF-A networks (without criterion variables) varied between genders. The most influential nodes (from the abbreviated version of the SELF-A) may be different between male and female students, underscoring the need for gender-sensitive approaches in intervention.

5. Discussion

The aim of the study was to explore the network structure of the SELF-A both as a standalone instrument and in relation to two criterion variables. In essence, the SELF-A network suggested that Items 12 and 17 were highly influential, meaning that changes in efficacy beliefs related to setting/rearranging priorities to allow more time for studying (Item 12) and associating/integrating details of a concept to enhance recall (Item 17) would be more likely to impact efficacy beliefs in other academic demands. Moreover, Item 7 seemed to associate with both criterion variables while Item 4, though not as consistently, seemed to associate with perceived stress. The impact of Item 7 on perceived stress was further supported by the Bayesian network. Considering the content of these items (Items 4, 7, 12, and 17) into account, it is arguable that efficacy beliefs in behaviors related to time and priority management (Item 12 and, to some extent, Item 4, which taps how students manage their weekly schedules from the phase "before the next class meeting") as well as concept association techniques or strategies (Items 7 and 17) may be of great importance for maintaining or even increasing overall levels of academic self-efficacy. Furthermore, efficacy beliefs in these behavioral domains may help students cope with academic stressors and enhance academic achievement. Beyond their direct implications for academic self-efficacy, it may be generalizable that mastering time management and concept association skills can help students effectively respond to academic demands and succeed in education.

In the context of Bayesian networks applied to psychopathology, McNally (2016) suggested three conditions under which researchers can be more confident in causal inference: (a) when the direction of the relationship between nodes is consistently observed (e.g., by bootstrap sampling); (b) when the relationship is conceptually and practically justifiable; and (c) when no other unmeasured variables could potentially affect the relationship. From 1,000 bootstrapped samples for the Bayesian network, the relationship between Item 7 and perceived stress has been observed 81.7% of the time, and 90.5% of the relationships observed evinced the direction from the former to the latter. This relationship is conceptually and practically reasonable, as students who possess strong efficacy beliefs regarding their learning processes are presumably less susceptible to stress, especially when learning new concepts. Despite the first two conditions being feasible, we could not ascertain the absence of unobserved variables affecting this relationship. For example, it is conceivable that learning skills themselves can be a common cause of both efficacy beliefs and stress, such that students with strong associative learning skills will have strong efficacy beliefs in leveraging these skills and experience low stress. Although a causal association could not be strongly entertained from the network, researchers can obtain an idea to generate a hypothesis from the relationship between Item 7 and perceived stress. Specifically, beliefs regarding one's learning skills and techniques (i.e., concept association or assimilation) may predict stress levels. Furthermore, beyond one's own beliefs, learning skills and techniques in and of themselves could be a target of interventions to ameliorate mental health difficulties among university students. This proposition has been partly supported by research evidence suggesting a relationship between associative learning techniques and learning performance (e.g., Blunt & Karpicke, 2014), but empirical investigations examining the relationship between learning techniques and mental health outcomes seemed to be lacking (except the work of Hossan and Islam [2019] with a narrow application).

From a theoretical standpoint, students who believe in their ability to use learning techniques or strategies (e.g., generating explanations, predictions, or concept maps; Brod, 2021) are more likely to integrate these techniques/strategies into their study routines. This practice, in turn, may help them achieve academic goals. However, research focusing primarily on self-efficacy in utilizing learning techniques/strategies has been rare. Recently, Greco et al. (2022) developed a scale assessing academic self-efficacy with eight dimensions, two of which tap efficacy beliefs related to learning techniques (i.e., learning strategies and skills for lessons). Although these dimensions yielded a positive relationship with exam outcomes, an in-depth examination of their item content revealed that they may reflect more on preparing for an exam than on applying learning techniques. Closely related, Ruiz-Martín et al. (2024) explored the relationship between learning techniques used by secondary school students and their cognitive and motivational factors. They found a positive association of academic self-efficacy with focusing, high elaboration, and retrieval practice, but not with low elaboration and spaced practice. Moreover, Karr and White (2024) investigated the relationship between academic self-efficacy and cognitive strategy use (e.g., attention and processing speed) in everyday life. Their findings demonstrated a small, positive relationship between academic self-efficacy and cognitive strategy use in both college students experiencing elevated levels of depression and anxiety and a non-clinical control group (correlation coefficients between .14 and .19). As various learning techniques can help students overcome academic demands and improve academic outcomes (e.g., Bisra et al., 2018; Brod, 2021), research on academic self-efficacy should further explore the role of efficacy beliefs in using learning techniques on learning behavior and academic achievement. To date, the relationship between academic self-efficacy and learning techniques has been blurred perhaps due to inconsistencies in item content. To illustrate, the academic self-efficacy scale used in Ruiz-Martín et al.'s study addressed primarily the "ability to successfully complete school tasks and assignments" (Ruiz-Martín et al., 2024, p. 7), rather than the ability to successfully use certain learning techniques. As a consequence, this research procedure led Ruiz-Martín et al. to contend that academic self-efficacy may likely result from prior academic success, and facilitating students in learning and using evidence-based learning techniques would improve their academic performance and, in turn, enhance their academic self-efficacy. While the above contention is reasonable given the authors' research procedure, we believe that refining the item content of academic self-efficacy scales to focus more explicitly on behaviors related to the application of learning techniques (perhaps as a distinct dimension) would provide further insight into the relationship between academic self-efficacy and academic outcomes.

From the perspective of the transactional model of stress and coping (Lazarus & Folkman, 1984), students may perceive academic challenges (as a primary appraisal of demands) and evaluate whether they have adequate learning skills and techniques to cope with such challenges (as a secondary appraisal of resources). Given this framework, it is arguable that well-developed learning skills/techniques can mitigate the negative effects of academic stressors, and students and educators may consider developing these skills/techniques as an adaptive coping mechanism. However, the role of learning skills/techniques as a coping strategy may often be overlooked in research on how students cope with academic demands. For example, the Academic Coping Strategies Scale (ACSS; Sullivan, 2010) contains 34 items measuring three dimensions of academic coping: approach, avoidance, and social support. Yet, none of its items directly address the concept of improving one's learning skills (the closest is Item 25 "put forth more effort into developing skills to master the problem", but this item does not specify what skills are). In addition, the Coping With Academic Demands Scale (CADS; Suldo et al., 2015) covers a wide range of coping strategies for academic demands, but it lacks a dimension focusing on using appropriate learning techniques to manage students' workload. Given this gap, fostering learning techniques and strategies could be added to academic coping scales, either as discrete items or as a coherent dimension within the family of approach coping. As both a belief in one's ability to use certain learning techniques and the actual ability to employ such techniques can be considered resources in the transactional model and, more broadly, within the stress and coping paradigm, students may benefit from equipping themselves with learning techniques in their toolbox, especially for handling academic demands and reducing stress levels.

In light of associations with the criterion variables, there were inconsistent findings between the undirected (psychological) network and the directed (Bayesian) network. Specifically, the relationships between Item 4 and perceived stress and between Item 7 and academic achievement were present in the psychological network but absent in the Bayesian network. This divergence was not surprising as these two networks relied on different algorithms to estimate their structures, and the 80% threshold in the Bayesian network seemed to be a more conservative criterion for relationship detection. With a bootstrapping technique to simulate the resampling distribution, we found that the relationships between Item 4 and perceived stress and between Item 7 and academic achievement were obtained in fewer than half of the bootstrapped samples (45.9% and 44.0%, respectively). However, among the subsets in which these relationships did emerge, more than four-fifths indicated a directional effect originating from the SELF-A items toward the criterion variables (80.9% and 86.1%, respectively). For comparison, the probability of a path between Item 7 and perceived stress was 83.4%, and in 90.5% of these cases, the direction flowed from the former to the latter. This pattern demonstrated analytic robustness in the estimated path, suggesting that the association between Item 7 and perceived stress remained stable across repeated model estimations. Hence, using a bootstrapping technique can be considered a corrective measure for addressing the uncertainty inherent in network-based estimations of directional relationships. Despite the relative uncertainty surrounding these associations, the roles of concept assimilation (Item 7) and concept clarification (Item 4) could not be overstated. Nevertheless, given that the content of Item 4 contains two additional elements (i.e., the temporal aspect "before the next class meeting" and the social aspect "by comparing notes with a classmate"), we could not determine whether these elements play a significant role in predicting perceived stress, above and beyond concept clarification. If these elements prove to be vital, they may advocate the importance of (efficacy beliefs in) time management (Bargmann & Kauffeld, 2023) as well as peer support (Hoferichter et al., 2022) in reducing students' stress levels, but a definitive conclusion could not be assumed at this stage.

In terms of building up students' academic self-efficacy, the role of priority and time management could not be overlooked. In hindsight, it may not be surprising that Item 12 ("change other priorities to have enough time for studying") was very influential in the SELF-A network as students who were good at (confident in) their priority/time management would be more likely to adapt effectively to academic challenges, leading to their confidence in other related tasks. This notion aligns with research suggesting that academic self-efficacy may mediate the relationship between time management behavior and stress among college students (Galindo-Domínguez & Bezanilla, 2021). Moreover, Bargmann and Kauffeld (2023) found that academic self-efficacy had positive relationships with time management and commitment to study, but a three-wave longitudinal analysis failed to find a mediating role of time management in the relationship between academic self-efficacy and commitment to study. The importance of priority/time management may be pronounced when students are required to engage in self-regulation on a weekly basis, as suggested via the content of Item 4 ("before the next class meeting"). Besides directly promoting time management skills, educators may consider structuring their courses in a way that compels students to manage their schedules right at the beginning of the semester with increasing difficulty (more workload) along the way. Small achievements in managing their time may promote a sense of efficacy beliefs in this task and help students cope with more challenging tasks throughout the semester.

Gender differences have been observed in various aspects of academic self-efficacy research. A meta-analytic study examining the mean differences in academic self-efficacy between male and female students revealed a small effect size ($g = 0.08$) favoring male students in terms of overall (as opposed to domain-specific) academic self-efficacy (Huang, 2013). When disaggregated by subject areas, the analysis revealed that male students had higher academic self-efficacy in the mathematics and computer domains, while female students had higher academic self-efficacy in the language arts domain. Furthermore, gender has been found to moderate the negative relationship between academic self-efficacy and stress in the context of learning mathematics, where the relationship was stronger (more negative) among female students (Ye et al., 2018). Although this study was limited by using the 8-item version of the SELF-A, it added to the literature by pinpointing the potential for gender-based differentiation in academic domains that may be impactful to students' self-efficacy systems. That is, while Item 18 ("go back to notes and locate the forgotten information") and Item 12 ("change other priorities to have enough time for studying") were central to the male network, the female network appeared to be most influenced by Item 14 ("motivate oneself for a disliked subject"). Somewhat interestingly, it has been suggested a potential trade-off between efficacy beliefs in different academic domains in the male network, wherein higher levels of self-efficacy in one domain (e.g., Item 14) corresponded with lower levels in another domain (e.g., Item 18) when controlling for other nodes. This pattern was not observed in the female network. Nevertheless, these gender-related differences described above should be treated as speculative, because no significant difference was observed when incorporating the two criterion variables into the network, and a stricter approach for network comparison (van Borkulo et al., 2023) should be adopted in future studies. It is important to note that these network comparisons were conducted using the abbreviated, 8-item version of the SELF-A. The other items were excluded following the process of validating an ultra-short, invariant version of the SELF-A for large-scale administration. It can be argued that, for item-level network comparisons to yield a result not contaminated by differential item parameters, the comparisons should be conducted using items from an invariant measurement model. When all 19 items of the SELF-A were included, no statistically distinct split networks were observed, indicating that (a) the overall network structure remained largely consistent across the levels of the splitting covariates, or (b) potential non-invariance in certain items may have attenuated observable differences.

Practical Implications

From a practical standpoint, we revisited the constraints imposed by different item content across academic self-efficacy scales. Within the scope of the SELF-A, two behavioral domains emerged as particularly important: managing time and priority, and using associative learning techniques. Therefore, to enhance academic self-efficacy and, in turn, promote academic achievement and mental health, interventions or guidelines focusing on these two behavioral domains seemed to be warranted. As suggested by Byars-Winston et al. (2017), performance accomplishments have been the most potent source of self-efficacy, and practitioners may design interventions to help students learn how to manage their time and schedule and how to use associative (and other) learning techniques, especially when studying new concepts. Warner and French (2020) have cataloged techniques to facilitate performance accomplishments such as graded mastery experiences and preparation for setbacks. In this vein, students may be encouraged to plan their study schedules on a weekly basis at the outset of the semester, when the workload is easily managed and adjustments are easily done if plans deviate. Likewise, they may be encouraged to gradually associate new concepts with pre-existing knowledge (also at the outset of the semester, when the material is not too much) and periodically use retrieval practice to assist recognition and recall. When deliberately incorporated into course syllabi or curricula, these mastery experiences can be largely self-administered by students with minimal assistance from psychologists and educators. Alternatively, a targeted intervention designed to promote time management and associative learning skills may be particularly useful for students who require additional support. It is important to note that the primary targets of these interventions/guidelines are behavioral outcomes such as rearranging and following schedules, as well as mapping and recalling concepts, whereas academic performance (e.g., test scores) and mental health outcomes should be considered secondary effects or by-products. Somewhat surprisingly, the importance of time management observed in this study has been congruent with research trends in Thailand, where academic procrastination has increasingly been recognized as a critical issue affecting students' academic functioning (Chatrakamollathas et al., 2022; Ratsameemonthon et al., 2018). Considering this convergence, it is plausible that within the Thai educational context, time management, whether it be conceptualized as a skill or as an aspect of self-efficacious beliefs, plays a pivotal role in shaping students' academic success. Accordingly, schools and universities may need to place great emphasis on developing students' time management competence and confidence, possibly by integrating these elements into co-curricular initiatives or extra-curricular programs.

To reiterate, in an ideal scenario with unlimited time and resources, practitioners could cover all behavioral domains from academic self-efficacy scales when designing an intervention. However, within the scope of the present study, some behavioral domains were more important in enhancing academic self-efficacy and predicting related outcomes than others. Practitioners seeking to expand the behavioral domains may consider adding self-motivating strategies (for a disliked subject), as this aspect appeared central to the female network. Among male students, domains related to time management and self-feedback (or self-evaluation and self-assessment) may be critical in their academic self-efficacy network. Other behaviors may be taking and summarizing notes, as well as studying with peers/classmates, because Item 6 ("condense notes down") and Item 8 ("be an effective study partner") were positioned in the shortest paths between the items with low means and academic achievement. Research has demonstrated that summarizing helped students catch and recall important propositions from a lecture more effectively than passive listening (Einstein et al., 1985). Further, peer-learning exercises have been identified as an effective learning technique in certain contexts (e.g., marketing education; Lastner et al., 2021). Although this study did not observe that the academic self-efficacy network differed based on students' years of study, cumulative research has indicated that students' academic self-efficacy tends to increase when they gain more experience in university (Bartimote-Aufflick et al., 2016). Hence, interventions and guidelines aimed at fostering academic self-efficacy may be best applied to first-year students at the start of university life.

Bartimote-Aufflick et al. (2016) also offered some pedagogical strategies to enhance academic self-efficacy; some of which may be aligned with the findings of this study such as using an appropriate amount of hints when applying a concept mapping technique (particularly with new topics) and providing "early low-risk opportunities" to complete small tasks (p. 1930, emphasis added).

At the university level, research has shown that institutional factors and campus environments can enhance students' academic self-efficacy and academic achievement (e.g., Cromley et al., 2016). For example, Museus et al. (2022) found that culturally supportive campus environments (e.g., humanized educational environments and cultural validation) were positively related to an increase in students' academic self-efficacy. Additionally, a review by Cromley et al. (2016) identified a range of institutional approaches to boosting academic achievement and retention among undergraduate students in STEM disciplines. An example of these approaches was the establishment of learning centers offering supplemental instructional programs designed to help students improve their learning and time management skills. In light of this study's findings, it may be advisable for the university or departmental administrative team to provide these activities (either mandatory or optional) to help students build confidence in applying these essential skills. These institutional policies may even be particularly advantageous in the context of Thai higher education, where such activities have been underprovided or overlooked (if not neglected altogether, it has been assumed that students have already acquired these skills from high schools). Perhaps these behavioral domains (learning and time management skills) have been found to be vital in this study because not all students are able to develop these skills by themselves, and those who already possess such skills are better equipped to manage academic demands.

Limitations and Future Directions

The approach of this study was exploratory, leveraging secondary data analysis to scrutinize the role of academic self-efficacy item content in predicting academic achievement and stress. Although a rigorous model selection method and a conservative criterion were used, we did not intend to establish a directed, causal relationship between academic self-efficacy and the criterion variables. Hence, the importance of efficacy beliefs in concept association and time/priority management, as well as their causal direction to academic achievement and stress, needs to be further examined using more robust methods, such as panel or time-series network analyses (Epskamp, 2020) or dynamic Bayesian networks (Needham et al., 2007), which explicitly model probabilistic dependencies over time with longitudinal data. Although learning strategies (e.g., Dunlosky et al., 2013) and time/priority management (e.g., Wolters & Brady, 2021) have been identified as common challenges among students across diverse educational contexts, the generalizability of the present findings should be empirically examined in other cultures and contexts, ideally with a more gender-balanced sample. Moreover, even though the item content in the SELF-A is broadly applicable to learning activities in higher education, there exist other academic self-efficacy scales that capture some interesting tasks in campus life. For example, in addition to the learning strategies and skills for lessons dimensions, the academic self-efficacy scale developed by Greco et al. (2022) contains other intriguing dimensions such as planning academic activities and working in groups. Furthermore, Luo et al. (2021) developed a 12-item scale measuring students' self-efficacy in STEM (science, technology, engineering, and mathematics) activities, with an emphasis on research and problem-solving. Also, a college self-efficacy inventory developed by Gore et al. (2005) taps three primary activities: class, social, and roommate. Although getting along with roommates may not be a universal experience among students (not all reside in dormitories), it is hard to deny that interpersonal conflicts with roommates can be a barrier for students to concentrate on studying or keeping up with schoolwork. Hence, an item-level analysis of efficacy beliefs in a diverse array of academic tasks and activities will contribute to a better understanding of the multifaceted role of academic self-efficacy in student success. Lastly, while Bandura et al. (1996) mentioned the idea that practitioners should attend to other facets of self-efficacy revolving around children's school experiences, this perspective can be extended to university students. For example, students' social self-efficacy (e.g., building and maintaining peer relationships) and self-regulatory self-efficacy (e.g., resisting peer pressure) or even parental academic self-efficacy (e.g., supporting and motivating students to continue higher education) may be important in fostering students to reach their full potential. Investigating the interplay between self-efficacy and behavior in multiple domains in higher education settings will ultimately benefit students, educators, psychologists, and institutional policymakers.

Conclusion

As a concluding remark, academic self-efficacy can be viewed as a multifunctional psychological construct that has been extensively investigated in relation to various academic outcomes such as achievement and engagement. However, research specifically targeting the behavioral manifestations of academic self-efficacy has been limited, as most studies have treated the construct as an aggregate variable rather than analyzing item-level responses that reveal the behaviors and strategies underlying students' efficacious beliefs in their learning processes. As a consequence, researchers and practitioners face limitations in translating existing research findings into effective interventions or guidelines for enhancing students' academic self-efficacy and related outcomes. It would be difficult to identify which specific behaviors or strategies within academic self-efficacy scales should be prioritized when designing such interventions/guidelines. Therefore, this study sought to address this gap by conducting a triangulation of item-level network analyses to identify the most critical behavioral aspects of academic self-efficacy that occupy influential positions within the network and serve as significant predictors of academic achievement and perceived stress. The overall findings revealed that behavioral aspects related to time/priority management, as well as technical detail association, were the most central components within the academic self-efficacy network, and that concept association strategies were reliable predictors of perceived stress. This knowledge can assist researchers and practitioners in developing targeted interventions to enhance academic self-efficacy and its desirable outcomes. In particular, it provides a basis for designing brief, resource-efficient interventions that focus on the most influential domains of academic self-efficacy. As performance accomplishments have been theorized and consistently demonstrated to be the most powerful source of self-efficacy (Bandura, 1977; Byars-Winston et al., 2017), interventions that encourage students to achieve small, incremental successes in managing their time and applying concept association strategies may be particularly effective. Such gradual, mastery-oriented practices would represent a more focused and evidence-aligned approach to strengthening students' academic self-efficacy compared to a broad or undifferentiated approach.

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APPENDIX

Table A1: Closeness Centrality and Expected Influence Indices

The SELF-A Items	Closeness Centrality	Expected Influence	
		One-step	Two-step
1. When you miss a class, can you find another student who can explain the lecture notes as clearly as your teacher did?	.00488	0.500	1.051
2. When your teacher's lecture is very complex, can you write an effective summary of your original notes before the next class?	.00561	1.031	1.854
3. When a lecture is especially boring, can you motivate yourself to keep good notes?	.00564	0.891	1.707
4. When you had trouble understanding your instructor's lecture, can you clarify the confusion before the next class meeting by comparing notes with a classmate?	.00555	0.870	1.638
5. When you have trouble studying your class notes because they are incomplete or confusing, can you revise and rewrite them clearly after every lecture?	.00574	1.001	1.976
6. When you are taking a course covering a huge amount of material, can you condense your notes down to just the essential facts?	.00547	0.900	1.743
7. When you are trying to understand a new topic, can you associate new concepts with old ones sufficiently well to remember them?	.00533	0.912	1.759
8. When another student asks you to study together for a course in which you are experiencing difficulty, can you be an effective study partner?	.00499	0.795	1.588
9. When problems with friends and peers conflict with schoolwork, can you keep up with your assignments?	.00540	0.765	1.529
10. When you feel moody or restless during studying, can you focus your attention well enough to finish your assigned work?	.00527	0.773	1.468
11. When you find yourself getting increasingly behind in a new course, can you increase your study time sufficiently to catch up?	.00557	1.032	1.985
12. When you discover that your homework assignments for the semester are much longer than expected, can you change your other priorities to have enough time for studying?	.00590	1.132	2.105
13. When you have trouble recalling an abstract concept, can you think of a good example that will help you remember it on the test?	.00538	0.841	1.729
14. When you have to take a test in a school subject you dislike, can you find a way to motivate yourself to earn a good grade?	.00570	0.971	1.944
15. When you are feeling depressed about a forthcoming test, can you find a way to motivate yourself to do well?	.00561	0.878	1.741
16. When your last test results were poor, can you figure out potential questions before the next test that will improve your score greatly?	.00536	0.890	1.806

17. When you are struggling to remember technical details of a concept for a test, can you find a way to associate them together that will ensure recall?	.00577	1.202	2.215
18. When you think you did poorly on a test you just finished, can you go back to your notes and locate all the information you had forgotten?	.00565	1.129	2.125
19. When you find that you had to "cram" at the last minute for a test, can you begin your test preparation much earlier so you won't need to cram the next time?	.00553	0.887	1.839

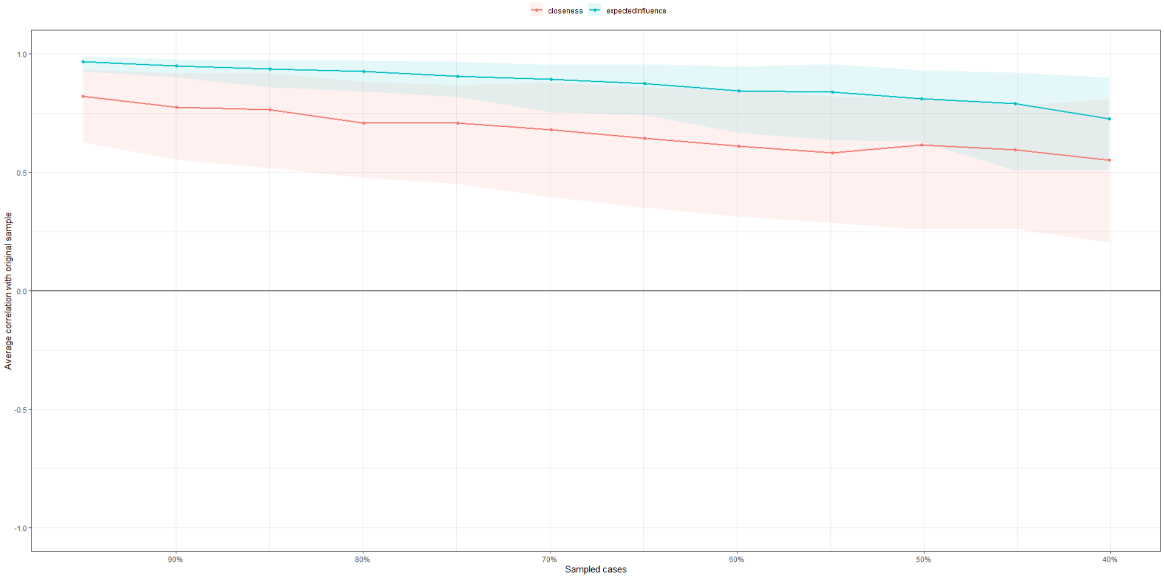

Figure A1: Centrality Index Stability

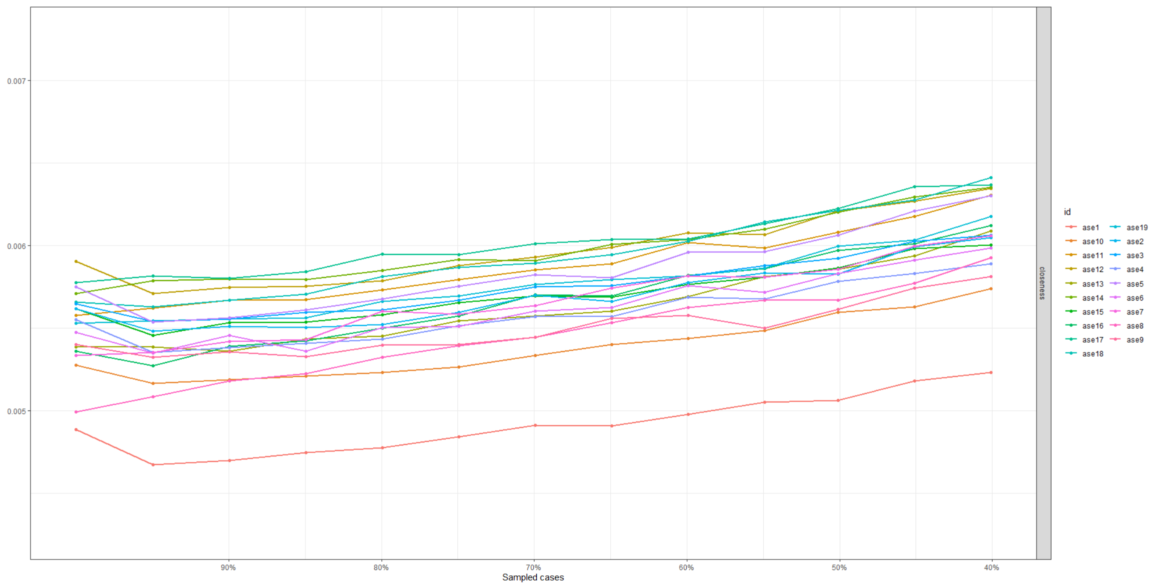

Figure A2: Node-wise Closeness Centrality Stability

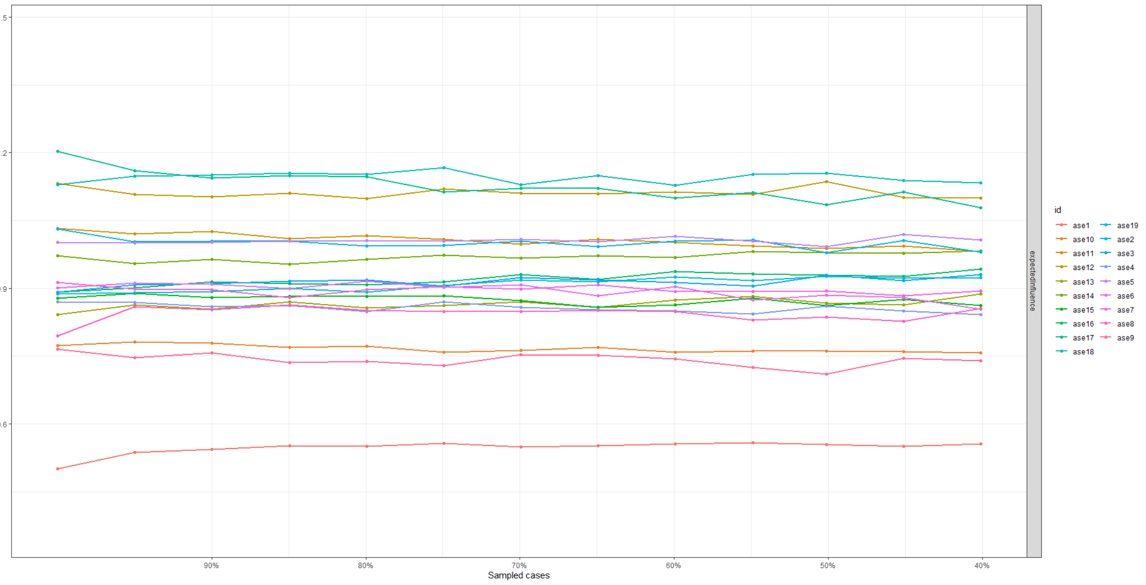

Figure A3: Node-wise Expected Influence Centrality Stability