

Article

At the center of it all: How personality amplifies centrality's effects on physics ability

Hans Muehsler^{1,*}¹ ETRA, Northern Illinois University, DeKalb, Illinois, USA

*Correspondence: Hans Muehsler (hmuehsler1@niu.edu)

Abstract: The social aspect of education is an important part of the learning process. In this study two research questions were asked to explore this idea. Social network analysis provided multiple measures of AP Physics 1 students' network centrality. These measures were used to predict physics achievement. Further, survey results measuring extroversion (EPI, $\alpha=.84-.94$), motivation (PGOS, $\alpha=.64-.83$), and self-efficacy (SOSESC, $\alpha=.94$) were used to determine students' personality characteristics. These personality results were used as moderators for the moderation analysis. The sample consisted of 106 students from a large, Midwestern, suburban high school taking AP Physics 1. Numerous centrality measures significantly correlated with physics achievement. Extroversion and self-efficacy increased the effect of centrality in most cases, whereas motivation did not change the centrality-achievement relationship. In most cases, having many, high quality connections was beneficial to learning physics, but personality characteristics must also be included in pedagogical decisions. Based on the results, teachers are strongly advised to account for personality and student connections when forming groups.

Keywords: Physics Education Research, Social Network Analysis, Personality, Moderation Analysis

How to cite this paper:

Muehsler, H. (2023). At the center of it all: How personality amplifies centrality's effects on physics ability. *Open Journal of Educational Research*, 3(2), 122–134. Retrieved from <https://www.scipublications.com/journal/index.php/ojer/article/view/661>

Academic Editor:

Ahmed El Hashash

Received: March 19, 2023

Accepted: June 27, 2023

Published: June 28, 2023



Copyright: © 2023 by the author. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (<http://creativecommons.org/licenses/by/4.0/>).

1. Introduction

It is well-established that students learn effectively through social interaction (e.g. [1]). One way to estimate the degree of social interaction within a group is through social network analysis. Measuring interactions between individuals in a classroom for a range of purposes is not a new idea; for instance, authors have measured student interactions related to sense of community [2], self-efficacy [3], and class performance [4, 5]. Bruun and Brewe [5] examined the effect of student interaction on academic performance at the post-secondary level in math and physics classes.

1.1. What is Social Network Theory?

Social network theory (SNT) is a large umbrella under which many other social learning theories exist. SNT is related to and works in concert with Vygotsky's sociocultural theory of cognitive development; from an educational perspective, SNT helps explain Vygotsky's theory by examining learner interactions and the construction of knowledge [2].

A social network analysis is a mathematical method of examining the social properties, connections, and interactions, along with the strength of these quantities between individuals within a group [2, 5–7]. In education, social networks have been used to demonstrate growth and types of student interactions [5]. It is within these interactions in the network that knowledge is created [8]. In short, social networks allowed researchers to examine the organization of a group from many perspectives, including how information and social norms were transferred [7, 9]. One way in to measure people's

interactions within a social network and ability to transfer information is through centrality.

Network centrality measures the relative importance of people in a network [5]; it is often related to the perception of power. These measures are a quantitative facet of connections between people [5]. Centrality measures are the primary metrics of a social network which identify the most prominent, or central, individuals in the group [6]; it is often the people with greatest centrality who disseminate information to the group [2]. These people also have the most connections [7]. Centrality measures may simply count the connections between people or may be probabilistic in nature; regardless, all centrality measures describe the relative importance of a person in a network [5]. Researchers classify individuals' connections or ties by their strength [6]. Further, it is assumed people influence each other within a network [5].

1.2. Theoretical Framework

It is believed SNT is related to connectivism. Connectivism is a learning theory which states that knowledge is held within a network of ties and learning is the ability to gather and use those ties to access information [8–10]. Learning is no longer acquiring a body of knowledge; learning is using social ties to access needed information and assessing what is important to consider, process, and find patterns and connecting nodes within the tapped information [9, 10]. This research will use aspects of Siemens' connectivist theory that intersect with social network theory, namely, knowledge is found in diverse opinions and learning is tapping and connecting with people and bringing this information back into the individual's network, thus creating a cycle of knowledge creation [8–10].

1.3. Literature Review

Being in a social network conveys many benefits to its members. If an individual is in a friendship network, the person increases the chances of accessing many resources and gathering information about tasks [11, 12]. The flow of information and social dynamic through central individuals maximized the benefits of the network for these people; being more central in a network, or greater centrality increases the effect of these benefits [11, 12]. The more centrally located a person is in the network, the greater the access of information from a variety of sources [11, 12]. This is a measure of the relative importance of a person in a network [5]. Centrality measures how well a person is connected or centrally located within a network [5, 6].

The definition of academic achievement varies by researcher. Some researchers emphasize the multifaceted nature of achievement, highlighting application of skills and transfer of knowledge [13, 14]. Other organizations underscore the need for student engagement [15]. However, the common theme throughout the perspectives is the need to demonstrate proficiency and performance in an academic area [13–15]. Academic achievement is the attainment of specified goals in an instructional environment [14]. Schools often define achievement as reaching cognitive goals or acquiring knowledge and understanding in a certain subject [14]. Institutions create indicators of achievement such as grades or performance level on an achievement test, in an effort of demonstrate the cognitive capacity of an individual [14]. The following themes demonstrate these characteristics.

1.4. Network Centrality and Achievement

The findings regarding the relationship of network centrality to student achievement is mixed. One view is that more social, centrally located students perform better academically. Studies have demonstrated increased centrality correlated significantly with better grades [6, 11, 12]. Other researchers found that only particular centrality metrics corresponded to student achievement measures (e.g. [5]). Likewise, students who were not found easily in the network earned lower grades [5]. In contrast, some authors

found centrality negatively impacted student success (e.g. 12). While most of the evidence points to network centrality as a positive predictor for student success, more research is needed to resolve these conflicts.

The structure of the social network and centrality of actors influences behavior within the network [16, 17]. These social norms often translate into behaviors affecting academic behaviors and outcomes [4, 16, 18]. For instance, Bond *et al* [4] stated friends' academic success influenced an individual's academic success. Bond *et al* continued by stating high achieving students often were more centrally located in a network and had an influence academically and behaviorally on other members. However, simply being in a high achieving network did not increase chances for success automatically [4]. In contrast, an individual in a low achieving network decreased achievement [4]. In essence, student centrality influenced peer academic behavior.

Research further indicated a diversity of networks with many interactions among constituents of the network, along with strong connections to other groups (to act as a broker of information), and a cohesiveness within the group contributed to increased academic performance [2, 6]. These characteristics of an information bridge or broker allowed an individual access to a great diversity of information; it is up to the bridging individual to determine the quality of information between sending the information along.

A student's activity within the network predicted student success. In general, increased activity and engagement with the network were correlated with increased meaning-making, resulting in increased student performance [5]. Further, students with many connections between groups were more active within the networks [2].

1.5. Personality Characteristics, Network Centrality, and Achievement

Emotional factors play a role in achievement. Extroversion describes people who are highly social, talkative, dynamic, and relate well to their environment [19–21]. These students draw their energy from being with people and actively search for social connections [21]. Self-efficacy is an important factor determining learning and achievement [22, 23]. Self-efficacy is one's belief in their ability to successfully accomplish a task; in some ways, it is similar to self-confidence [22–24]. This self-perspective is strongly related to science competencies [23]. Motivation is a person's desire to learn and maintain their learning status [25, 26]. Motivation is also related to the student's persistence, interest, approach to learning, and self-efficacy [27, 28]. Overall, motivation is an important predictor of school achievement, roughly at the same level as intelligence [29].

The reviewed literature was mixed regarding the influence of extroversion on achievement. Oluwadamilare and Adekunle [19] found a significant relationship between extroversion and physics achievement. In contrast, O'Connor and Paunonen [30] found a negative relationship between extroversion and academic achievement. Finally, Kalra and Manani [31] did not find a significant relationship between extroversion and achievement.

As with extroversion and achievement, the literature was mixed regarding extroversion and network centrality. Olguin and Gloor [32] found extroversion was positively correlated with certain measures of centrality centralities. In contrast, Klein *et al's* [33] research found that extroversion did not predict centrality and Cross *et al* [34] stated the connection between personality traits such as extroversion and network position was a "myth." Cross *et al* [34] elaborated stating that network position is determined by a person's "intentional behaviors" (p. 73).

A number of authors have researched the relationship between self-efficacy and network centrality. For instance, Dou *et al* [3] found a relationship between students' network position and changes in the source of self-efficacy. In a different study, Vardaman *et al* [35] demonstrated self-efficacy's mediating role with network centrality and interpretations of controllable change. Brewe *et al* [36] and Fencl and Scheel [37] found

significant relationships between self-efficacy and final grades in introductory physics courses.

A number of authors have researched the relationship between motivation and network centrality. In one study, Li and Stone [38] found significant relationships between scholastic motivation and network indices as well as centrality measures. Further, the higher the value of a student's centrality, the stronger the student's academic motivation was [39].

While research has been conducted regarding social network measures and achievement with many groups, little research was found measuring the effect of student interaction at the secondary level among high-achieving students in an Advanced Placement (AP) physics. Further, little literature was found regarding the relationship between student interactions and personality characteristics with physics ability. This study aimed to address this gap in the literature.

To address this research gap, a set of research questions was developed. These questions are:

- 1) Are different measures of centrality related to student ability?
- 2) Is network centrality moderated by personality characteristics?

2. Materials and Methods

For this study, AP Physics 1 students in a large, Midwestern, affluent, suburban high school were sampled. In this study, 59% were male and 41% were female. Of the 158 available students, 106 students fully participated in the study. Students identifying as white comprised 46%, 45% of the students identified as Asian; the remaining students were African-American and Latino. Further, 79% of the students were juniors, 11% were sophomores, and the remainder were freshmen and seniors.

Inspired by Bruun and Brewé's [5] research methodology, for the centrality aspect of the study, students were provided with a list of all participating students and asked to indicate which students they interacted with and how many times during the week regarding problem solving and conceptual discussions. The survey was administered through Qualtrics at approximately 10 day intervals.

To capture the personality aspect of the students, a battery of surveys was used. First, a demographic survey was administered. This survey contained items related to the participant's year in school, race and ethnicity, gender, previous math and science classes taken and the respective grades for those classes, as well as the current math class and present grade in the class. Other administered surveys were Eysenck's Personality Inventory (EPI) to measure introversion and extroversion, the Physics Goal Orientation Survey (PGOS) to measure motivation, and the Sources of Self-Efficacy in Science Courses survey (SOSESC) to measure self-efficacy. These surveys were administered over the course of two weeks, as time permitted and so students did not experience fatigue responding to so many items in one sitting.

Scores from the final exam were used to capture the achievement aspect of the students. The final exam consisted of AP Physics 1-based items. The test consisted of 21 multiple choice items, three of which were multiple response; the multiple response items were discarded from the study due to their complex nature. The exam also consisted of three free-response items; these items were not included in the study because of the subjective nature in scoring.

2.1. Reliability and Validity

One demographic and four personality surveys were administered to participating students, as well as a final exam. The EPI demonstrated satisfactory test-retest reliability with alpha between .84 and .94 [40]. Eysenck [40] identified three factors and Chapman [41] found significant correlations between the identified subscales. Further, Chapman [41] used factor analysis to find 6 facets for the extroversion scale to demonstrate construct

validity. Eysenck [40] also stated the EPI was closely related to the MPI demonstrating convergent validity. To add further validation to the EPI, comparisons were made between independent judges' reviews of known extroverts and the results from the scale [40]. The SOSESC is a 33-item inventory in which students rated their confidence regarding physics classroom situations on a 5-point Likert scale [37]. Estimated reliability for alpha ranged from .68 to .8 for each subscale and .94 for the entire inventory [37]. The SOSESC underwent expert review to demonstrate content validity and a CFA was performed to ensure the categories of items aligned with the way students felt about the questions for construct validity [37]. The PGOS is a 19-item survey intended to take less than five minutes to administer. Lindstrøm and Sharma [42] reported values of Cronbach's alpha ranging from .64 to .83. The authors used CFA and stated a sufficient number of items with loadings greater than or equal to .6 were present, meeting Streiner's [43] requirements. Overall, four stable factors were identified, with expected and acceptable loadings, demonstrating construct validity [42]. The PGOS underwent cross-validation with student interviews from focus groups, as well as expert review for content validity [42].

For the 18 multiple choice items on the final exam, the items were in two primary constructs. Cronbach's alpha for each construct was found to be .489 and .581. Item difficulty ranged from .3 to .9 and point biserial correlations ranged from .23 to .51. Although alpha was low, previous research has shown an alpha above .5 or near .6 may have acceptable reliability in social science and educational research [44, 45]. Further, a low alpha may be an artifact of a smaller sample size [46]. The exam items were created and agreed upon by subject matter experts; however, a CFA was not performed due to the small number of participants.

IRT scaled scores from the exam were used as the dependent variable. IRT scaled scores were estimated by the item characteristic curve; this curve predicts the probability of a correct answer by the participants' ability and the item difficulty [47].

2.2. Measures of Social Networks

Many measures of social networks exist. One of the most common measures for individuals is centrality. A person who is more central or involved has many ties or connections [7]. Centrality comes in a variety of measures. The first, and the simplest, is degree centrality. Degree centrality is a measure of how well a node is directly connected to other nodes, the activity of the person or node, and the person's importance in the network [6, 7, 48]. This measure of centrality is useful for finding well-connected or popular individuals who may hold the most information or who could find out information easily [48].

Betweenness centrality is how many times an individual connects pairs of other individuals [6]. Betweenness is useful for identifying people who influence the flow of information in a network and quantifies how often a node acts as a bridge for the shortest path between two other nodes [48]. Each connection is of equal weight and communications flow along the shortest path [7].

Closeness centrality indicates how connected an individual is to the entire network, connecting to others through a small number of paths [2, 6]. People with high levels of closeness can quickly interact with other people and may be more effective and efficient at disseminating information to others [7].

Eigenvector centrality is a measure of the node's influence based on the number of connections to other nodes and also accounts for the connections' links; eigenvector centrality finds people with influence over the entire network [48]. Eigenvector centrality is a good "all-around" network scoring mechanism, according to Disney [48].

A number of other measures of centrality also exist. Information centrality also is based on betweenness centrality and is similar to eigenvector and degree centrality, although it is a measure of closeness [7]. It focuses on information from all paths beginning

on a specific person [7]. Power centrality considers a person's power as a function of the connections' or alters' power [49]. Stress centrality is similar to other measures of centrality in that it measures the potential ability of a node to control the flow of information in a network based on the shortest paths through the person in question [50]. PageRank centrality is similar to eigenvector centrality in which a person's local connections and the connections' ties determine the score for the node [5, 48].

Finally, clustering measures the amount nodes cluster in a network [51]. The local clustering coefficient measures how close a node and its neighbors are to forming a clique [51]. This measure is found by comparing the number of actual ties to a node to the number of possible ties [51].

To assess the personality dimensions using the surveys, the survey instructions were followed. Generally, this amounted to summing scores across responses for each participant. Prior to data collection, IRB approval was sought and gained (NIU IRB approval protocol number HS22-0193)

2.3. Analysis

After data were collected from each of the surveys and the final exam, the data were screened for missing data, outliers, and unusual values. If participants had more than 5% missing responses on a survey, their responses were discarded [52]. After these cases were removed, 106 cases remained. For the remaining cases, missing values were imputed using the "mice" [53] package for R [54].

Student connection information was used in the Social Network Analysis and Visualizer (SocNetV) application [55]. SocNetV is free, open-source software that calculates numerous properties of the entire network and for the individuals in the network. Because some cooperating teachers administered the network surveys only once, the ties were unweighted and the ties were considered reciprocal, as was true in over 80% of the cases. It is acknowledged that some information was lost in "flattening" the data, however.

Once the students' centrality measures were calculated, personality scores for each survey were calculated according to their respective manual's directions. The centrality measures, personality scores, and demographic information were imported into SPSS v. 26 [56].

Next, simple linear regressions of IRT scores on each of the centrality measures and personality characteristics scores were computed. Moderation analyses also were performed to examine the effect of personality characteristics on the regression. To examine differences between areas in the spread of the independent variable, cutoff values were set at -1, 0, and 1 standard deviations. The moderation analyses were performed using the PROCESS macro [57]. The variables in the moderation analyses were grand-mean centered.

3. Results

First, the raw network data between the conceptual and problem solving was examined. No major differences between the two sets of raw data were found when comparing ties between students; less than 3% of the ties were different between the two sets of data. Comparisons were made by aligning the students between each set of data and determining if the value of the two sets of intersections were identical. Further, the data was "flattened" and assumed reciprocated for this study, becoming a 1 or a 0 representing a connection or no connection. For this reason, only the conceptual set of network of data was considered for this study. The minimum power for the set of analyses was .905, based on a medium effect size of $f=0.15$, $\alpha=.05$, $N=100$ (minimum sample size), with 3 predictors [58].

3.1. Relationships Between Network Centrality and Physics Ability

Simple OLS regressions were performed to examine the relationship between network centrality and physics ability. In all cases, regressions were screened for outliers, influential or high leverage points, and autocorrelation, as well as normality and heteroscedasticity in the residuals. A table of the statistically significant results of the simple regressions is presented in Table 1. Significance was set at $\alpha=.05$. Most relationships between network measures and physics ability were weakly significant. Clustering had a negative correlation with physics ability.

Table 1. Relationships Between Network Measure and Physics Ability

Network Measure	R	p_{cor}	b	t	p_t
Betweenness	.265	.003	0.003	2.758	.007
Closeness	.215	.013	458.0	2.248	.027
Influence Range Closeness	.228	.009	4.464	2.390	.019
Eigenvector	.209	.016	5.948	2.163	.033
Information	.287	.001	0.367	3.054	.003
Degree	.315	<.001	0.069	3.387	.001
Power	.242	.006	0.035	2.543	.012
Stress	.338	<.001	0.003	3.666	<.001
PageRank	.350	<.001	88.02	3.810	<.001

3.2. Personality Traits' Moderation on the Effect of Network Measures on Physics Ability

To determine if personality characteristics moderated the direct effect of network measure on ability, several moderation analyses were performed. The classical, but generalized, moderation diagram is shown in Figure 1. In this case, X is the network centrality measure, M is the personality characteristic measure, and Y is physics ability.

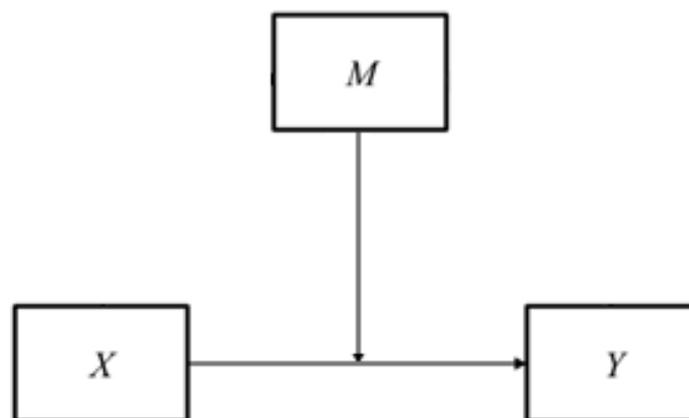


Figure 1. General moderation conceptual diagram.

Significant results from the moderation analyses are presented in Table 2. Some values were included because they were marginally non-significant or had a confidence interval that nearly indicated significance, given the range of values. Only motivation, extroversion, and self-efficacy were found to be significant moderators of network measures and physics ability.

Table 2. Personality moderation results.

Interact. CI	[-0.257, 6.65]	[-8.49, 173.4]	[0.019, 1.56]	[-0.612, -0.080]	[-0.005, 0.216]	[-4.401, 245.9]
Interact. <i>p</i>	0.069	0.075	0.045	0.011	0.061	0.059
Interact. <i>t</i>	1.837	1.8	2.033	-2.58	1.898	1.914
Interact. <i>F</i>	3.373	3.239	4.132	6.656	3.604	3.663
Interact. <i>r</i> ² Change	0.027	0.029	0.035	0.057	0.027	0.027
Interact. <i>df</i> ₂	101	101	101	101	101	101
Interact. <i>df</i> ₁	1	1	1	1	1	1
<i>p</i>	0.0001	0.005	0.002	0.002	<.001	<.001
<i>F</i>	6.854	4.044	4.723	4.607	8.786	9.241
Model <i>r</i> ²	0.217	0.144	0.158	0.157	0.258	0.268
<i>df</i> ₂	101	101	101	101	101	101
<i>df</i> ₁	4	4	4	4	4	4
<i>M</i>	Motivation	Extroversion	Extroversion	Extroversion	Self-efficacy	Self-efficacy
<i>X</i>	Clustering	Closeness Centrality	Influence Range Closeness	Clustering	Degree Centrality	PageRank

After the significant moderations in [Table 2](#) were found, follow-up assessments were performed for each of the areas of data. The significant moderations were segmented by those above one standard deviation (SD), those between 1 and -1 SD, and those below -1 SD. Graphs demonstrating the interactions between those regions were examined along with the range for the significant regions using the Johnson-Neyman technique.

Overall, for low ability students, as clustering increased, physics ability decreased. Average and high motivation did not change the relationship between clustering and physics ability. Further, high levels of extroversion positively and more strongly increased the effect of closeness centrality and influence range closeness on physics ability than lesser levels of extroversion. In contrast, for high levels of extroversion, increased clustering tended to decrease physics ability; likewise, for students with very low levels extroversion, clustering had a positive effect on physics ability. When considering self-efficacy, students with average and high levels of self-efficacy positively increased the effect of degree centrality and PageRank on physics ability.

4. Discussion

This research filled the gap regarding student network centrality and achievement at the secondary level in Advanced Placement Physics. Further, the gap regarding the moderation by personality characteristics on this relationship has been filled. The results and explanations of the results follow.

4.1. Network Measures and Physics Ability

The results from the first research question yielded results in agreement with several authors. Bruun and Brewe [5] found highly significant correlations between their considered network centrality measures and grades. The current study's conclusions generally agree with Bruun and Brewe's [5] in that students more actively participating

in peer interactions tended to earn higher grades or have higher ability levels. The correlations found in this current study are all similar in magnitude, but small. Further, students who were easy to find in a network or who had increased information flow had higher ability levels, in agreement with Bruun and Brewe [5].

Clustering, which considers how close an individual is to a closed group, or clique, had a negative relationship with physics ability. This finding was not unexpected—the closer a person was to being in a clique, the less new information flows into the group. This finding, however, contrasts with Nichols and White's [18] results in which they found those students in a clique experienced greater achievement. It was unfortunate there was not more diversity in responses from this present study between the conceptual and problem solving networks to verify Nichols and White's [18] finding. Putnik *et al* [6] found larger degree centrality and betweenness led to higher quality work. If higher quality work may be a proxy for higher ability, this current research supports Putnik *et al.*'s findings; in fact, betweenness and degree centrality had two of the larger correlations with physics ability.

4.2. Moderation of Physics Ability and Network Centrality by Personality Characteristics

When considering the effect of moderation, motivation significantly moderated the clustering and physics ability relationship. For low motivation students, clustering and physics ability were positively related. This may have occurred due to the indication of tighter groups formed; while less information was flowing into these groups from other students, the clustering appeared to have helped these students succeed. These less motivated students at least had other students to exchange ideas; these groups may have also been closer friends that helped less motivated students along. Kriegbaum *et al* [29] also found motivation was an important predictor of achievement. While not directly comparable because this study did not seek to determine the relative importance of personality characteristics on achievement, motivation was found to have the largest coefficient of the three personality predictors of physics ability; this finding was in contrast to Chai *et al* [25], Howard *et al* [59], and Kriegbaum *et al* [29] who all found motivation played a smaller role in predicting scientific ability compared to other psychological factors. Highly extroverted students demonstrated more physics ability as influence range closeness increased compared to other groups. This effect may be because more highly extroverted students had additional connections bringing more information their way. This finding ignored the effects of motivation. Highly extroverted students also demonstrated more physics ability as closeness increased. These highly extroverted students may be more connected to the entire course network naturally and can gain information quickly, increasing their physics ability. Similar to Olguin *et al* [32] and in contrast to Klein *et al*, [33], network centrality extroversion was positively correlated with numerous centrality measures. Further, the findings in this study were in agreement with Oluwadamilare and Adekunle [19] and in contrast to O'Connor and Paunonen [30] and Kalra and Manani [31] in that extroversion positively predicted physics achievement.

Clustering was the exception to this trend in extroversion moderation. For increased levels of extroversion, increased clustering tended to decrease physics ability. If strongly extroverted students were in tighter clusters, they did not receive as much new information flowing into their localized network, decreasing their physics ability. It was also possible that being in a tighter cluster may impugn these students' natural tendencies for extroversion, reducing their physics ability. Further, for students with very low levels of extroversion, increased clustering had a positive effect on physics ability. For students in this very low range of extroversion, forming a clique may have been the best way to gain ability; this social structure may fit their personality better. Watts and Strogatz [51] and Asendorph and Wilpers [60] reported similar findings regarding clustering and physics ability.

Self-efficacy was the final significant moderator considered. Students with average and high levels of self-efficacy had a significantly positive effect on the relationships between degree centrality and PageRank network measures and physics ability. Students with strong self-efficacy beliefs and who had connections to strong networks exhibited increased levels of physics ability. Students who had average levels of self-efficacy performed in a similar way, but with lower levels of physics achievement. More connections of higher quality may mean more feeding information into the student's localized network and this increased amount of information reinforces the student's belief in their ability. These findings are in general agreement with Lin *et al* [61] and Chang *et al* [47] in that students with high levels of emotional factors and self-efficacy scored higher in scientific literacy and general performance, which may be related to ability. More specifically, Brewe *et al* [36] and Fencil and Scheel [37] found significant relationships between final grades in introductory physics and level of self-efficacy, similar to this current study's findings. Further, Dou *et al* [3] found a relationship between self-efficacy and network position, similar to that found in this research.

5. Conclusion

This study examined the moderating effects of centrality measures on the personality characteristics-physics ability relationship and the moderating effects of personality characteristics on the centrality measures-physics ability relationship. Overall, this study found network measures impacted physics ability, supporting Vygotsky's work and the theory of connectivism. Further, extroversion, motivation, and self-efficacy all moderated the existing relationships between network centrality measures and physics ability. Clustering had a generally negative effect on physics ability when moderated by extroversion, except for weakly extroverted students. In general, the higher value ranges of the moderators saw the most positive impacts on physics ability.

5.1. Limitations

The main weakness in the study regarded data collection. This study relied on student surveys to assess with whom they talked, the topics of discussion, and the frequency and direction of contact during the week. This method required students to remember their discussions. Students may conflate their social network contacts and discussions with on-task discussions, making it difficult to disentangle the two networks.

5.2. Recommendations

First, educators must take into account student personality traits and connections within the class when forming groups. If educators form groups for the students, ensuring students with appropriate connections and personality traits will maximize learning for the student in question as well as the other members in the group. For instance, it may be prudent to place a student with low motivation in a tightly clustered group to facilitate the exchange of ideas. At the same time, placing an extroverted student in a tightly clustered group should be avoided; extroverted students may be able to bring more information into the group. Further, a student's connections can amplify their self-belief which can increase learning outcomes. A teacher can account for personality characteristics to place students in groups to amplify their performance.

Second, educators must monitor students' course progress. If students are failing to achieve in physics ability, educators may encourage students to reach out to other students and seek their perspectives; the students will learn from each other by tapping the resources of the network. Educators also may reorganize groups to account for changes in connections and previously unseen personality traits as the course evolves.

Third, students should be encouraged to not be alone in class, even if the students are not naturally extroverted. Finding a small group with which to work may help the student's physics ability, as demonstrated in this research. Educators are encouraged to

monitor the networks to ensure correct and appropriate information is moving through their course networks.

Data Availability Statement: Anonymized data available upon request.

Conflicts of Interest: The authors declare no conflict of interest.

References

- [1] Vygotsky, L. *Mind in Society*; Harvard University Press: Cambridge, MA, **1978**.
- [2] Dawson, S. A study of the relationship between student social networks and sense of community. *Journal of Educational Technology & Society*, **2008**, *11*, 224–238.
- [3] Dou, R.; Brewe, E.; Zwolak, J.P.; Potvin, G.; Williams, E.A.; Kramer, L.H. Beyond performance metrics: Examining a decrease in students' physics self-efficacy through a social networks lens. *Phys. Rev. Phys. Educ. Res.*, **2016**, *12*, 1–14.
- [4] Bond, R.M.; Chykina, V.; Jones, J.J. Social network effects on academic achievement. *The Social Science Journal*, **2017**, *54*, 438–449.
- [5] Bruun, J.; Brewe, E. Talking and learning physics: Predicting future grades from network measures and Force Concept Inventory pretest scores. *Phys. Rev. ST Phys. Educ. Res.*, **2013**, *9*, 1–13.
- [6] Putnik, G.; Costa, E.; Alves, C.; Castro, H.; Varela, L.; Shah, V. Analysing the correlation between social network analysis measures and performance of students in social network-based engineering education. *Int J Technol Des Educ*, **2016**, *26*, 413–437.
- [7] Wright, A. *Centrality and prestige*, **April 13, 2005**.
- [8] Western Governors University (WGU). Connectivism learning theory. <https://www.wgu.edu/blog/connectivism-learning-theory2105.html#close>.
- [9] Dyer, G. The big three constructivism, constructionism and connectivism. <http://thinkspace.csu.edu.au/gdyer/2014/06/01/the-big-three-constructivism-constructionism-and-connectivism/> (Accessed September 13, 2018).
- [10] Siemens, G. Connectivism: A learning theory for the digital age. *International Journal of Instructional Technology & Distance Learning*, **2005**, *2*.
- [11] Baldwin, T.T.; Bedell, M.D.; Johnson, J.L. The social fabric of a team-based M.B.A. program: Network effects on student satisfaction and performance. *Academy of Management Journal*, **1997**, *40*, 1369–1397.
- [12] Cho, H.; Gay, G.; Davidson, B.; Ingraffea, A. Social networks, communication styles, and learning performance in a CSCL community. *Computers & Education*, **2007**, *49*, 309–329.
- [13] EL Education. The three dimensions of student achievement. <https://eleducation.org/resources/el-dimensions-of-student-achievement-in-el-schools> (Accessed April 29, 2023).
- [14] Steinmayr, R.; Meißner, A.; Weidinger, A.F.; Wirthwein, L. Academic Achievement. In: *Distance learning*. Lowenthal, P., Rice, K., Rich, S., Walters, S., Eds.; Oxford University Press: [New York], **2017**.
- [15] Law Insider. Student achievement definition. <https://www.lawinsider.com/dictionary/student-achievement> (Accessed April 29, 2023).
- [16] Mihaly, K. *Do more friends mean better grades? Student popularity and academic achievement*; Report: Washington, D.C., **March 2009**.
- [17] Yang, H.-L.; Tang, J.-H. Effects of social network on students' performance: A web-based forum study in Taiwan. *OLJ*, **2019**, *7*, 93–107.
- [18] Nichols, J.D.; White, J. Impact of peer networks on achievement of high school algebra students. *The Journal of Educational Research*, **2001**, *94*, 267–273.
- [19] Oluwadamilare, A.J.; Adekunle, A.M. Partial least square modeling of personality traits and academic achievement in physics. *Asian Journal of Assessment in Teaching and Learning*, **2021**, *11*, 77–92.
- [20] Hakimi, S.; Hejazi, E.; Lavasani, M.G. The relationships between personality traits and students' academic achievement. *Procedia - Social and Behavioral Sciences*, **2011**, *29*, 836–845.
- [21] Psychology Today. Extroversion. <https://www.psychologytoday.com/us/basics/extroversion> (Accessed April 29, 2023).
- [22] Lu, Y.-Y.; Smith, T.J.; Hong, Z.-R.; Lin, H.-S.; Hsu, W.-Y. Exploring the relationships of citizens' scientific interest and self-understanding to their learning enjoyment and self-efficacy in science. *Current psychology (New Brunswick, N.J.)*, **2022**, 1–13.
- [23] Tsai, C.-Y.; Li, Y.-Y.; Cheng, Y.-Y. The relationships among adult affective factors, engagement in science, and scientific competencies. *Adult Education Quarterly*, **2017**, *67*, 30–47.
- [24] Bandura, A. Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, **1977**, *84*, 191–215.
- [25] Chai, C.S.; Lin, P.-Y.; King, R.B.; Jong, M.S.-Y. Intrinsic motivation and sophisticated epistemic beliefs are promising pathways to science achievement: Evidence from high achieving regions in the East and the West. *Frontiers in psychology*, **2021**, *12*, 1–14.

- [26] GUILLOTEAUX, M.J.; Dornyei, Z. Motivating language learners: A classroom-oriented investigation of the effects of motivational strategies on student motivation. *TESOL Quarterly*, **2008**, *42*, 55–77.
- [27] McGrew, K. Beyond IQ: A model of academic competence and motivation. <http://www.iapsych.com/acmcewok/Academicmotivation.html> (Accessed 4/29/20223).
- [28] Stover, J.B.; La Iglesia, G. de; Boubeta, A.R.; Liporace, M.F. Academic Motivation Scale: Adaptation and psychometric analyses for high school and college students. *Psychology Research and Behavior Management*, **2012**, *5*, 71–83.
- [29] Kriegbaum, K.; Becker, N.; Spinath, B. The relative importance of intelligence and motivation as predictors of school achievement: A meta-analysis. *Educational Research Review*, **2018**, *25*, 120–148.
- [30] O'Connor, M.C.; Paunonen, S.V. Big Five personality predictors of post-secondary academic performance. *Personality and Individual Differences*, **2007**, *43*, 971–990.
- [31] Kalra, R.K.; Manani, P. Effect of social networking sites on academic achievement among introverts and extroverts. *Asian Journal of Social Sciences and Humanities*, **2013**, *2*, 401–406.
- [32] Olguin, D.O.; Gloor, P.A.; Pentland, A. In: *AAAI Spring Symposium: Human Behavior Modeling*, **2009**.
- [33] Klein, K.J.; Lim, B.-C.; Saltz, J.L.; Mayer, D.M. How do they get there? An examination of the antecedents of centrality in team networks. *Academy of Management Journal*, **2017**, *47*.
- [34] Cross, R.; Nohria, N.; Parker, A. Six myths about informal networks — and how to overcome them. In: *Creating value with knowledge*. Prusak, L., Lesser, E., Prusak, L., Eds.; Oxford University Press, **2004**; Vol. 43; pp. 67–75.
- [35] Vardaman, J.M.; Amis, J.; Dyson, B.; Wright, P.M.; Randolph, R. Interpreting change as controllable: The role of network centrality and self-efficacy. *Human Relations*, **2012**, *65*, 835–859.
- [36] Brewe, E.; Sawtelle, V.; Kramer, L.H.; O'Brien, G.E.; Rodriguez, I.; Pamelá, P. Toward equity through participation in Modeling Instruction in introductory university physics. *Phys. Rev. ST Phys. Educ. Res.*, **2010**, *6*.
- [37] Fencel, H.; Scheel, K. Engaging students. *Journal of College Science Teaching*, **2005**, *35*.
- [38] Li, M.; Stone, H.N. A social network analysis of the impact of a teacher and student community on academic motivation in a science classroom. *Societies*, **2018**, *8*, 68.
- [39] Shin, H.; Ryan, A.M. Early adolescent friendships and academic adjustment: examining selection and influence processes with longitudinal social network analysis. *Developmental psychology*, **2014**, *50*, 2462–2472.
- [40] Eysenck, H.J.; Eysenck, S.B.G. *Manual of the Eysenck personality inventory*; Hodder & Stoughton, **1964**.
- [41] [Chapman, B.P.; Weiss, A.; Barrett, P.; Duberstein, P. Hierarchical Structure of the Eysenck Personality Inventory in a Large Population Sample: Goldberg's Trait-Tier Mapping Procedure. *Personality and Individual Differences*, **2013**, *54*, 479–484.
- [42] Lindström, C.; Sharma, M.D. Development of a physics goal orientation survey. *International Journal of Innovation in Science and Mathematics Education*, **2010**, *18*, 10–20.
- [43] Streiner, D.L. Figuring out factors: the use and misuse of factor analysis. *Canadian journal of psychiatry. Revue canadienne de psychiatrie*, **1994**, *39*, 135–140.
- [44] Hinton, P.R. *SPSS explained*; Routledge: London, New York, **2004**.
- [45] Moss, S.; Prosser, H.; Costello, H.; Simpson, N.; Patel, P.; Rowe, S.; Turner, S.; Hatton, C. Reliability and validity of the PAS-ADD Checklist for detecting psychiatric disorders in adults with intellectual disability. *Journal of intellectual disability research: JIDR*, **1998**, *42* (Pt 2), 173–183.
- [46] El-Uri, F.I.; Malas, N. Analysis of use of a single best answer format in an undergraduate medical examination. *Qatar Medical Journal*, **2013**, *2013*, 3–6.
- [47] Chang, M.; Singh, K.; Mo, Y. Science engagement and science achievement: Longitudinal models using NELS data. *Educational Research and Evaluation*, **2007**, *13*, 349–371.
- [48] Disney, A. Social network analysis 101: Centrality measures explained. <https://cambridge-intelligence.com/keylines-faqs-social-network-analysis/>.
- [49] Butts, C.T. Find Bonacich power centrality scores of network positions. https://rdrr.io/cran/igraph/man/power_centrality.html.
- [50] Max Planck Institute for Informatics. NetworkAnalyzer online help. <https://med.bioinf.mpi-inf.mpg.de/netanalyzer/help/2.7/#stressDist>.
- [51] Watts, D.J.; Strogatz, S.H. Collective dynamics of 'small-world' networks. *Nature*, **1998**, *393*, 440–442.
- [52] Tabachnick, B.G.; Fidell, L.S. *Using multivariate statistics*, 4th ed.; Allyn and Bacon: Boston, Mass., **2005**.
- [53] van Buuren, S. *Multivariate Imputation by Chained Equations (mice)*, **2021**.
- [54] R Foundation for Statistical Computing. *R: A language and environment for statistical computing*; Vienna, Austria, **2022**.
- [55] Kalamaras, D. *Social network analysis and visualization software: SocNetV*, **2021**.
- [56] IBM Corp. *IBM SPSS for Windows*; IBM Corp.: Armonk, NY, **2019**.
- [57] Hayes, A.F. *PROCESS*, **2022**.
- [58] Buchner, A.; Erdfelder, E.; Faul, F.; Lang, A.-G. *G*Power*, **2020**.
- [59] Howard, J.L.; Gagné, M.; Bureau, J.S. Testing a continuum structure of self-determined motivation: A meta-analysis. *Psychological bulletin*, **2017**, *143*, 1346–1377.
- [60] Asendorph, J.B.; Wilpers, S. Personality effects on social relationships. *Journal of personality and social psychology*, **1998**, *74*, 1531–1544.

- [61] Lin, H.-S.; Hong, Z.-R.; Huang, T.-C. The role of emotional factors in building public scientific literacy and engagement with science. *International Journal of Science Education*, **2012**, *34*, 25–42.