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Research Article

A Dynamic Network Analysis of an L2 Motivation System: The Role of Central Relational Links

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ABSTRACT

This study employed dynamic network analysis to investigate the role of central relational links within the motivational system of 59 English for Academic Purposes (EAP) learners. The findings suggest that these links are best understood as central relational nodes, which act as hubs that give structure and stability to the network and enable the flow of information between clusters of factors within the second language (L2) motivation system. Results also indicate that while the centrality values of these nodes are dynamic, fluctuating from week to week, these nodes are relatively stable in their roles. Furthermore, although the motivational trajectory of individual learners may differ significantly and various motivational factors and their connections appear, disappear, and reappear in the system, the stability of central relational nodes facilitates an emergence of recurring patterns. This suggests that a shared socio-cultural and educational context may reduce the unpredictability of L2 motivation.

Keywords: L2 motivation, complex dynamic systems theory, network analysis, motivational factors

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INTRODUCTION

The word "motivation" in many languages is closely related to the idea of movement and action. As is the case with many European languages, the English word "motivation" comes from the Latin word *movere*, "to move." The Greek word for motivation, *κίνητρο*, comes from *κῑνέω*, which means "to move, start, or arouse;" it is this root that the words kinetic and kinesthetics are derived from. In Chinese, *动机*, "motivation," is a compound word made of two characters that mean "move, movement, action" and "machine," respectively.

Motivation as an engine of action is an apt metaphor. Second language (L2) motivation plays an essential role in successful language learning as it serves as both an initial impetus and continual driving force of effort (Dörnyei & Ryan, 2015, p.72). It is a part of a dynamic and relational system inseparably intertwined with a specific temporal-spatial context (Hiver & Larsen-Freeman, 2019; Ushioda, 2009, 2015). Furthermore, it is often perceived as being multifaceted and comprised of psychological constructs, such as the ideal and ought-to L2 selves (Dörnyei, 2009), as well as others, including instrumental and integrative motives (Gardner, 2001; Gardner & Lambert, 1959, 1972). A student's motivational disposition to put in effort to learn a language emerges from the interaction of these motivation constructs with other language learner-specific factors, such as cognition and affect, physical and emotional wellbeing, as well as a myriad of external factors both in and outside of the language classroom (Pack, 2021).

In order to further the field's understanding of L2 motivation as a complex and dynamic phenomenon, scholars have called for the use of network analysis (NA) as a way to disentangle the interwoven nature of the motivational system (Hiver & Papi, 2019; Mercer, 2015). As Mercer (2015) notes, NA may help in "retaining a holistic, interconnected, situated perspective" that "enables a degree of simplification, which makes researching the system, especially the dynamics of the system and the relationships within it, more empirically manageable" (p. 80). Hiver and Papi (2019) suggest that NA may help in identifying key interactions that shape emergent outcomes of L2 motivation, as it goes beyond measuring isolated elements and focuses on central relational links. Indeed, a NA approach to researching L2 motivation makes sense given that "networks are the prerequisite for describing any complex system" (Barabási, 2003, p. 238) and that "complexity theory must invariably stand on the shoulders of network theory" (Barabási, 2003, p. 238).

Despite multiple calls for the use of NA and the potential of networks to provide useful maps for analyzing and understanding complex systems (Caldarelli & Cantanzaro, 2012, p.41), such as L2 motivation, NA remains an underutilized research methodology within the field. Potential reasons accounting for this may be difficulties arising from creating a L2 motivation network, the lack of formal training on NA methods and analytical software in postgraduate applied linguistics programs, and/or the demanding and complex nature of complex dynamic systems theory (CDST) informed research design.

To answer calls to use NA for exploring relational links of L2 motivation and to increase general awareness of NA in the field, the authors previously explored the patterns and relational links of a network of motivational factors that 59 English language learners identified while keeping a motivational journal for 10 weeks (Kiss & Pack, 2022; Pack & Kiss, 2022). The current study continues with this endeavor; while the initial studies explored the patterns and relational links of a composite network of motivational factors over 10 weeks, and their interconnectedness with individual learners, the current study investigates the dynamic nature of relational network links. In doing so, we answer the call of Al-Hoorie et al. (2021) to "cast a wider net that recognizes and accommodates various crucial environmental factors" in order to "conceptualize the *dynamic, diachronic transformational nature* of the language learning experience in context" (p. 145, emphasis added). The central research question therefore guiding the current study is the following: How do the central relational links' operations within an L2 motivation network change over a period of 10 weeks?

Before reviewing the extant literature, and in order to avoid confusion, we believe it prudent to first clarify the usage of the term *factor* throughout this paper. Given L2 motivation research is heavily influenced by the field of psychology, the term *factor* is frequently used to describe psychometric latent variables, such as *instrumentality* or *integrativeness*. Yet, the term *factor* is also widely used in a more general and broad sense (e.g., the quote above from Al-Hoorie et al., 2021) that is more akin to "an element or constituent, esp. one which contributes to or influences a process or result" (Oxford University Press, 2022). In this paper, we use the term to refer to any element, inside or outside the language classroom, that is viewed by the language learner as having an influence on their motivation.

LITERATURE REVIEW

L2 Motivation and CDST

L2 motivation is an emergent property of a complex dynamic system (CDS) that includes many agents and elements inside and outside of the language learner, as well as formal and informal language learning contexts (Pack et al., 2021). The elements within this system (and its nested systems) are interconnected and nonlinear, resulting in the system (and the L2 motivational disposition that emerges from it) being sensitive to initial conditions, adaptive and non-final, and dependent on internal and external resources (de Bot & Larsen-Freeman, 2011). Because of a number of reasons, including sensitivity to initial conditions and variations in context, motivational factors affect students in different ways, thereby rendering it difficult to make generalizations about motivators and demotivators in second language acquisition (SLA) (Kikuchi, 2017; Pack, 2021). Motivational factors rarely act in isolation, and their possible assemblage at any moment may steer L2 learners' motivational system towards a specific attractor state that results in a particular motivational disposition (Kiss & Pack, 2022). Hiver (2015) explains that an attractor state is "a patterned outcome of self-organisation (…) and it can emerge without anyone purposely directing or engineering it" (p. 21). Yet, while language teachers cannot control L2 motivation directly, they can influence it by introducing elements and feedback into the system that push the L2 motivational system towards a more positive state (Pack & Kiss, 2022). No learner's motivational state is final, as new elements can perturb or jolt the system from temporary attractor states from which positive or negative motivational dispositions emerge.

The characteristics of L2 motivation as a CDS described above present a challenge for researchers. As de Bot and Larsen-Freeman (2011, p. 11) noted: "How can you study a system and its subsystems when everything is interconnected?" One answer to that is that NA does exactly that; it investigates the interconnectedness of elements in a complex system. Therefore, NA has been proposed as a potential way forward in CDST-guided L2 motivation research as it affords a degree of simplification and makes researching system dynamics more empirically manageable (Mercer, 2015). Additionally, it provides a way to identify central relational links that play a role in key interactions that shape emergent motivational dispositions, a needed enterprise in the field of L2 motivation according to Hiver and Papi (2019).

Network Analysis

NA involves leveraging network graphs and statistics to explore the relationships between elements that a particular network is composed of. It has been used in a wide variety of fields, including economics, epidemiology, security, neuroscience, social networking, and management, amongst others (Barabási, 2016).

A network is "a catalog of a system's components" (Barabási, 2016, p. 5). Network graphs are algorithm-generated visualizations of the relationship of these components. Individual elements within the network are represented as vertices or nodes (small circles), while links are denoted by edges (lines) that join pairs of nodes (Brandes & Erlebach, 2005). Graphs can be directed, where relationships between nodes are defined (e.g., X is the predecessor of Y), or undirected, where relationships are unknown and/or not defined. Graphs can also be weighted, meaning that numerical values (weights) are assigned to the nodes or edges. Different graph-generating algorithms afford researchers with varying perspectives of the same data. The Yifan Hu algorithm, for example, pulls connected nodes together, while unconnected nodes are pushed apart; this is useful when researchers want to identify nodes that are not well-connected to larger groups (Cherven, 2013, p.28). The OpenOrd algorithm, on the other hand, was designed to enable researchers to better distinguish between clusters (i.e., groups of nodes that act similarly) (Gephi Tutorial Layouts, 2011).

In addition to providing visualizations in the form of network graphs, NA software affords researchers with network statistics that provide insights into the relationships and dynamics of the system; they present the empirical evidence from network data from which findings and conclusions can be drawn. Only a few of the most common and essential statistics will be highlighted here (see Barabási, 2016, Cherven, 2013, and Padilla & Locke, 2014 for explanations of additional network statistics).

A key property of each node is *degree*, which represents the number of links that the node shares with other nodes. The *weighted degree* is the strength of these links; the more frequently two nodes are linked, the higher the weighted degree. *Betweenness centrality* is a measure of "the level at which any given node serves as a bridge connecting other nodes (Cherven, 2013, p. 75); nodes with high betweenness centrality likely play important roles in the network as they play central hubs by which information travels through the network. *Eigen centrality* is a measure of "node importance in a network based on a node's connections; the sum of the centrality measures of all nodes connected to a node" (Padilla & Locke, 2014).

The value, then, of leveraging network graphs and statistics to investigate L2 motivation, is that these tools afford researchers with the ability to investigate the dynamic interconnectedness of the motivational CDS and the central relational links that steer motivation towards a particular attractor state (i.e., an emergent positive or negative motivational disposition).

L2 Motivation Studies That Leverage Network Analysis

Despite the aforementioned affordances, few studies have leveraged NA to investigate L2 phenomena, including L2 motivation. Furthermore, the literature tends to utilize two types of NA: social network analysis, which investigates concrete links among learners, and psychological network analysis, which focuses on estimated connections among psychological constructs (Freeborn et al., 2023). In other words, there is a clear distinction in research between the study of physical systems, for example, learners and their interactions and connectedness, ideational systems, and the relationships among unobservable psychological constructs. However, such categorization may run against the principles of CDST, argues Davis (2008, p. 53), who says that "the ideational is inseparable from the material." Therefore, in the study of L2 motivation there should be room for networks which build upon and make use of the interconnected nature of different systems, including psychological and social networks.

Bernstein (2018) explored how the centrality of learners in classroom interaction might affect vocabulary gains of pre-kindergarten English language learners. Results suggested that higher levels of centrality (i.e., a central place in classroom interaction) did not equate to greater improvement in vocabulary and syntactic complexity. Li and Stone (2018) investigated the centrality and motivation of 95 Grade 8 students. They found that centrality significantly correlated with higher academic motivation. Additional studies have leveraged NA to explore social interaction while studying abroad (Isabelli-García, 2006), the effects of online social networks on L2 communication (Paul & Friginal, 2019), and English for Academic Purposes (EAP) students' willingness to communicate in an L2 (Gallagher & Robins, 2015).

Two studies explore networks of motivational factors. Ngan and Law's (2015) used NA to investigate learning motivation factors in online computer programming courses. Making use of hierarchical graph clustering, directed connectivity graphs, dendrograms, and multiple regressions, they explored a network comprised of motivational factors such as individual attitudes and expectations, a clear direction, reward and recognition, punishment, challenging goals, the effect of the e-learning system utilized, efficacy, and social pressure and competition. They conclude that NA may allow for strategic prioritization of the most important learning motivation factors.

Kiss and Pack (2022) investigated the structure, connectivity, and central relational links of a network that was composed of L2 motivational factors identified by 59 university EAP learners who kept motivation journals for 10 weeks. They identified five major clusters in the highly connected network: assignments, classes, being and feeling (moods and emotions), the specific time of day or day of the week, and students' physical health and well-being. They found that some factors that play central roles in the network are not the most cited or even most connected, but the connections they do share are crucial in allowing the formation of bridges that link distinct communities of nodes together. Lastly, they found that motivating and demotivating factors are well connected to each other; they argue that the push and pull of factors of different polarities is likely a major reason why the motivational system remains dynamic. They conclude that motivational factors rarely act in isolation and that learners' motivational disposition comes from the unpredictable interactions and possible assemblage of motivational factors at any given moment.

However, given that the L2 motivational factor network utilized in Kiss and Pack's (2022) study was essentially a composite of factors identified over 10 weeks, the study was not able to explore the dynamicity of the central relational links it identified. The current study aims to add to the findings of the previous study by exploring how the central relational links dynamically change over 10 weeks. Put another way, while the initial paper provided a computerized tomography (CT) scan of the entire 10 weeks as a whole unit of time, the current paper makes use of multiple layers of CT scans to investigate the dynamicity of the central relational links as they, and if they, change over time. Investigating how central relational links behave in a motivation system may allow more control over the system and could empower language teachers to direct learners' motivational disposition to more motivated states. Liu et al. (2011, p.167) point out that a "dynamical system is controllable if, with a suitable choice of inputs, it can be driven from any initial state to any desired final state within finite time." This makes one wonder if an L2 motivation network can be controlled or directed and whether identifying central motivational links would help determine what input could drive the system towards more motivated dispositions.

METHODOLOGY

Participants

The data used in this study were collected as part of a larger research project (Pack, 2021) that aimed to investigate the motivational dynamics of first-year EAP students in an English-medium instruction (EMI) university and to identify salient motivating and demotivating factors. Sixty university freshmen participated in the study, but one student dropped out due to other commitments. They were recruited by means of a non-probability voluntary response self-selection sampling method. The majority of students were Chinese nationals, with five international students being exceptions. Students were allocated into five different tutorial groups, based on their subject areas and language proficiency. Students were between the ages of 18 and 20, had intermediate (B1/B2) English proficiency levels according to the Common European Framework of Reference for Languages (CEFR; Council of Europe, 2023), and came from a wide variety of majors. There were 13 male students and 44 female students and two who did not register their gender. In order to protect the learners' identity, each learner was assigned a code, for example, D1, where the letter indicated the tutorial group and the number referred to a specific student in that group.

Data Collection Procedures

Data were collected over the period of 10 weeks by means of motivational journals that students completed in their second semester. Before data collection, the motivational journal was first piloted with eight Year 2 EAP students, who used it for a period of four weeks. Minor changes in the instructions and organization of the motivational journal were made based on feedback provided by these students. Using the final version of the motivation journal, the 60 participants then recorded daily their willingness to study EAP. This was done by selecting a motivation level on a five-point scale (0 – *very demotivated*, 1 – *fairly demotivated*, 2 – *slightly motivated*, 3 – *fairly motivated*, 4 – *very motivated*). Similar to Waninge et al.'s (2014) research, the students were asked to reflect on the following questions when they indicated their motivation level: (1) How much effort do I want to put into learning EAP? and (2) How much do I enjoy learning EAP? In addition, students were asked to provide a brief explanation for selecting a particular motivation level, thereby identifying motivating or demotivating factors that influenced their willingness to study. Lastly, students reflected weekly by commenting on why their motivation went up, down, or remained the same over the week. The motivation journals provided a blend of narrative frames and a series of still images about the learners' motivation at regular intervals and enabled them to write about anything inside or outside their learning context that affected their motivation to learn EAP. It served as a guidance and support in capturing the learners' thoughts and feelings.

Data Coding Procedures

Using NVivo 12 (Lumerivo, 2017), motivation journals were coded in several cycles of coding. The process started with basic coding for case, motivational level, and changes in motivation level compared to the preceding journal entry. These were coded together with the week and day (e.g., Week 2, Tuesday) of the entry which allowed both the tracking of motivational levels over the 10 weeks as well as the creation of a dynamic network by the use of timestamps.

The second and third cycles of descriptive or thematic coding (Saldaña, 2009) focused on identifying motivational factors in the students' journal entries. Three independent coders worked on the data; to ensure reliability, one complete 10-week journal was coded by all and used as the basis of calculating inter-rater reliability. This was established by calculating a Kappa coefficient of 0.96, well above the 0.85–0.89 benchmark suggested by Saldaña (2009). Coding similarities and differences were discussed and a code book was created for the next stage of coding where each coded another five journals. A Kappa coefficient of 0.95 indicated high inter-rater reliability. The rest of the data were then divided equally to be coded individually. The coding process resulted in 1,022 thematic codes, which we refer to as motivational factors, and 59 cases or student codes. An example of the thematic coding is offered below:

> Yesterday I encountered some individual issues and they were successfully dealt with, giving me much courage. A good night's sleep also helped a lot. Although homework was heavy and challenging, I managed to complete them all effectively. [(Student D1, motivation journal, Week 2, Monday; motivation level 4 (*very motivated*)].

This entry was coded under the following thematic codes: a) Assignments, coursework, homework, and projects, b) Being or feeling (mood and emotion), c) Finishing an essay, assignment, project, homework, d) Courage, e) Having a good sleep or enough sleep, f) Positive emotion, g) Physical health, h) Rest and sleep, i) Being or feeling challenged, j) Difficult assignment, k) Hardship in personal life. Although it is clear that not all codes are thematically motivational, for example, Having a good sleep, we included them in our analysis because the participants felt they were important to understand how their state of motivation changed or remained the same over a period of time.

Data Analysis Procedures

A self-reported L2 motivational network consisting of the 1,022 motivational factors was created by means of Gephi 0.9.2 (Bastian et al., 2009), a NA software platform for exploring data through statistical measures and network visualizations. While beyond the scope of this paper to detail the specifics of how Gephi network analysis works (e.g., how centrality statistics are calculated), readers interested are encouraged to read Grandjean (2015) and AxU Platform (2020). The network was filtered according to week number, thereby providing 10 freeze frame pictures of the network for each week of the study. Dynamic network analysis (DNA) is applicable when the network is characterized by frequent changes over time (Cherven, 2015). For this study, using the case coding of the data, we created a dynamic topological network in which "nodes can change positions, and appear or disappear at specific time intervals" (Cherven, 2015, p. 244). Matrix coding queries in NVivo 12 revealed each thematic code, as well as timestamps. These together provided information about the strength of a node in any given week. For example, the motivational factor (node) Hardships in personal life was coded as <[1.0, 2]; [3.0, 2]; [4.0, 2]; [8.0, 2]; [9.0, 1]> where the first numbers within the square brackets indicate the week when the factor was mentioned in the complete dataset and the second numbers refer to its strength, (i.e., how many times it was coded in that particular week).

The self-reported L2 motivational network can be visualized as an overlay of two interconnected networks, in which the direction of edges was defined; edges between motivational factors were non-directed as it was impossible to determine how motivational factors impacted each other. In the example given above we do not know if finishing an essay, assignment, project, homework was the result of rest and sleep, positive emotions, or the courage to deal with a personal issue; therefore, directional links between them cannot be established. What is certain, however, is the fact that all these motivational factors were somehow linked and together they pushed the learner (C1) into a 4 – *very motivated* state which made it possible to set directed links (edges) between motivational factor and student nodes. Although the research participants in the study came from different tutorial groups, this information, or the link between individual learners, was not indicated in the network. As L2 motivation is interpreted as dynamically changing, dependent on the learner's willingness and effort to learn, it is seen as an emergent property of the complex, dynamic, and non-linear interaction of elements (factors), internal and external to the language learner. Given that learners' psychological states, including motivational disposition, are influenced by social agents and factors, both the physical and the ideational worlds they inhabit, we believe a combination of social and psychological factors would offer the most comprehensive picture to understand their L2 motivation.

In order to investigate changes that occurred in the network over the 10-week period of the research, we selected three weeks for closer investigation; these were Weeks 3, 7 and 9. The reason for focusing on these weeks is that they are at least 2 weeks apart and they represent markedly different intensities in learning requirements and challenges students face during the semester.

Data collection started after the add/drop period of the first week, in order to avoid unnecessary fluctuations in student participants. Week 3 of the research, therefore, is a critical period when students have settled into their courses and have started to work towards completing their first assignments. Week 7, which is the semester break, was chosen specifically to see how the absences of classes impacted their motivation. At this point students have received feedback on assignments and projects, yet a significant amount of effort to complete coursework is still required, which conceivably could push motivation to a positive or negative state. Finally, Week 9 is the last week when assignments still play a part in students' EAP studies; some learners are nearly finished with their major assignments while others might have already completed them.

In order to provide data that illustrate the dynamic nature of motivational change, two learners, A10 and C3, were randomly selected for further analysis; their motivational levels, position in the network, and journal entries were used to offer more insight into the nature of the L2 motivational systems. A10 was a male Chinese civil engineering student and C3 was a female Chinese architecture student. There were 33.7 codes recorded on average in student A10's motivation journal each week, while there were 33.8 codes for student C3. This indicates that these students completed their journals for all ten weeks and that, on average, they provided the same amount of qualitative data.

FINDINGS

In order to create a baseline from which comparisons of differences and changes in the network from week to week can be drawn, the OpenOrd algorithm was used to generate an overall composite picture of the L2 motivation network (see Figure 1). The visualization features of node size, color, and positioning, were included, based on the suggestions of Venturini et al. (2014). Grey nodes represent motivational factors while white nodes indicate students. Red edges denote a connection between motivational factors while green edges represent the link between motivational factors and students. The size of the nodes indicates their degree or the number of connections they have. The network graph was filtered to display degree values between 20 and 200, in order for the most connected nodes to stand out, while ensuring the less connected ones remain visible.

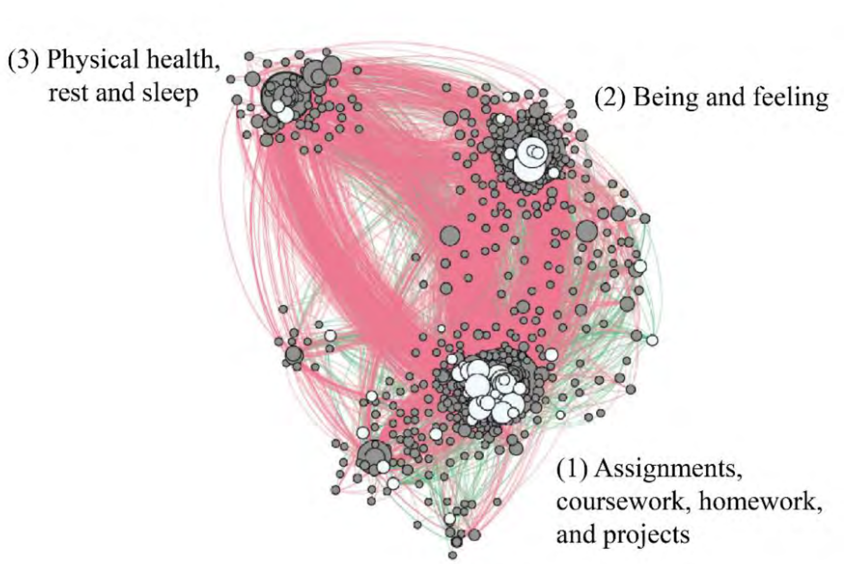
There are three major communities or clusters and several minor communities, with other nodes scattered amongst these clusters. The three major forces that drive the L2 motivation factor network are assignments, moods and emotion, and physical health. These communities are strongly linked to each other, suggesting that these connections form the central relational links within the network and that changes in any of these forces will impact the others, thereby moving the motivational system towards a more motivated or demotivated state.

The OpenOrd layout organized some (but not all) students into specific communities. This likely suggests that certain students are more prominently influenced by some motivational factors than other factors. The students represented by larger nodes wrote more in their motivation journals, which is one reason why they share more connections to motivational factors. However, it appears that the amount of data they have provided in the journal does not seem to indicate differences in their motivational dispositions or in their level of motivation at any given time. Therefore, writing more does not equate to higher motivation levels.

Students whose nodes were in the same community tended to be from the same tutorial group as indicated by the letters (i.e., 'A', 'B', etc.). The grouping of student nodes into clusters is a result of their connections with motivational factors as identified by the algorithm, given no relationships between individual students or groups of students were coded by the authors. This suggests that shared experiences in the classroom may play an important role in shaping the trajectory of individual learners' motivation in a similar direction, despite the myriad of external factors in students' individual lives.

Altogether there are 1,087 nodes in the network, 1,028 are motivational factor nodes and 59 are student nodes. Of the motivational factors, however, only 27 of these appear in the network each week. These factors are: Physical health; Rest and sleep; Assignments, coursework, homework and projects; Good desires; Desire to learn; Being or feeling (moods and emotions); What students did (relating to studying); Busy; Classes; Other modules; Exams or tests or quizzes or assessment; Negative emotions; Desire (lack of – negative); Essay or paper; EAP class; Tired; Time or days; Being relaxed or relaxing; Weather; Math class; Friends; Seminar; Vacation and travel; Weekend; Study; No class; and International English Language Testing System (IELTS) or Test of English as a Foreign Language (TOEFL). Another 18 nodes appeared in the network in nine of the 10 weeks, and a further 26 appeared in eight of the 10. These 71 factors provided the backbone of the network on a weekly basis. On average, 315 motivational factors appear in the network each week, which indicates fluctuation among the total 1,087 factors that exert an influence on the system.

Figure 1. *OpenOrd Layout of the L2 Motivation Network*



Note. The nodes are resized according to the number of connections they have with other nodes (node size: 20–200).

Table 1. *Student Nodes Located in Major and Minor Communities*

Major and Minor Communities	Student Nodes
Assignments, coursework, homework, and projects (major)	A4; B3; D1–5, 7, 9–10, 12, 14–15, 18; E1–2
Physical health, rest, and sleep (major)	A2; D8,13, 20; E9–10, 15
Being or feeling (moods and emotions) (major)	B1, 4; D17; E3, 6
Teachers, clubs (minor)	A14; D11; E4, 12
Time or days (minor)	C1, 6; E16–17
Lack of desire, do not want to study (minor)	A9; C4–5; D16, 19; E8
Good desires (minor)	A3, 5–8, 10–13, 15–17; B2; C3; E5, 7, 11

Figure 2. *Network Graph Filtered to Show Highest Betweenness Centrality Nodes in the Network*

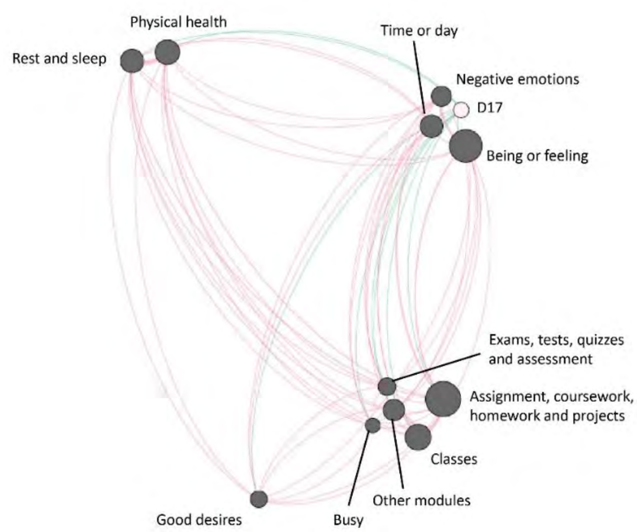


Table 2. *Betweenness Centrality Values in the Complete L2 Motivational Network*

Nodes	Betweenness Centrality
Assignments, coursework, homework, and projects	94994.49
Being or feeling (moods and emotions)	66455.64
Time or days	35467.30
Classes	32331.85
Physical health	27035.99
Good desires	24923.80
Exams or tests or quizzes or assessment	22715.21
Rest and sleep	21831.60
Busy	18099.88
Negative emotions	16030.44
D17	15749.49

Figure 3. *OpenOrd Layout (20–200 Node Size) of the L2 Motivational Network at Week 3 (292 Factors), Week 7 (207 Factors), and Week 9 (215 Factors)*

In order to visualize some of the most important nodes, a filtered graph was created which shows the 10 most connected motivational factors in the network and one student node (Figure 2). A few important observations can be made from Figure 2 concerning the positions and the connection between the most influential motivational factors in the network. First, given that data from the motivational journals show that assignments and assessments in general acted as a positive motivational force for the learners (Pack et al., 2021), it is not surprising that good desires, which also exerted a positive impact on the learners' motivation, is in close proximity. The OpenOrd algorithm is force-directed, which means that nodes and communities that are connected are pulled to each other, while those not linked are pushed apart. The spatial arrangement of the most connected nodes in the network, therefore, indicates how strongly they are connected to each other. At the other end of the network, far from the factors which have the potential to move learners' motivational disposition into a positive orientation, lie Physical health and its partner, Rest and sleep. These factors were generally cited when the students' motivation took a negative turn, indicating that health and lack of rest and/or sleep were cited as significant reasons for their diminishing motivation. It is interesting to note, however, that the positive and the negative motivational forces in the network are strongly connected to each other, and therefore, exercise a push and pull effect that results in steering the system towards a motivated or demotivated state, but not allowing it to settle in these states for an extended period of time.

In between these polarized motivational forces lie a multitude of factors associated with Being and feeling, which refer to the students' inner world of feelings, attitudes, moods, and other related emotional and psychological factors. While Assignments and Assessment (external factors) and Health and Rest (physical factors) are skewed as being primarily motivating or demotivating forces in the network, Being and feeling (i.e., affective factors) can exert both positive and negative forces on learners' motivation, enhancing or dampening the effects of the major motivating or demotivating forces at play in the L2 motivational system. In fact, Being and feeling was the second most connected motivational factor in the network as shown in Table 2.

Yet, motivation as a CDS is prone to dynamic changes, which is highlighted by the difference in the number of motivational factors (1,028) in the complete network and the much lower number of factors (an average of 315) that appear in the system on a weekly basis. Therefore, the question must be raised: are the prominent forces of assignment and assessment, physical health, and being and feeling present as driving forces across a longer time period, or are they simply the accumulated result of a large amount of data? The graphs representing Weeks 3, 7, and 9 (see Figure 3) suggest that although their network structure shows similarity, they are different from each other in significant ways.

Week 3 L2 Motivation Network

The network at Week 3 contained the highest number of motivational factor nodes (292) (see Figure 4). Within the Week 3 network graph are eight distinct communities (see Figure 4). One community, Entertainment, is spread around the clusters of Being and feeling and Time or day, and is therefore more difficult to identify in the graph. It is also clearly visible that the three major motivational forces mentioned earlier (i.e., Assignments and assessments, Physical health and Rest and sleep, and Being or feeling) are clearly present: Assignments and assessment holding 22.08%, Physical health 13.1%, and Being and feeling 19.09% of the nodes.

The particular placement of student nodes within the network, in combination with data from the journals, provided insights into how various factors in the motivational network push and pull against each other, ultimately giving rise to varying motivation levels throughout the week. The node for student A10, for example, is located between Lack of or negative desires and Something happy or good, and the rest of the network. The week's average of his reported motivational levels was 2.57, which is between *fairly demotivated* and *slightly motivated* levels. In his journal, he wrote that spending time playing mobile phone games took time away from studying. Yet, he acknowledges that this entertainment increased his general mood and happiness, at least at the beginning of the week. "Played some mobile phone game and got a good grade in this game," he wrote on Tuesday (motivation level 4 – *very motivated*). However, as time passed, he felt that he was not giving as much attention to his learning as he should: “Get up late so that I don’t have enough time to prepare myself” (Thursday), and “So much homework to do” (Sunday). His motivation level slumped drastically to level 1– *slightly demotivated* on Saturday when he took part in a mobile phone gaming competition and lost; “it took me so much time to prepare for it” and “study mission didn’t finish,” he noted. The negative feeling of losing the game, in spite of extensive preparation, and the realization that he was not prepared for the following week had an impact on his motivation.

In contrast, the node of student C3 is placed in close proximity to the cluster of Good desires, which may have played a role in her higher average motivational level of 3.42 (which is between *fairly motivated* and *very motivated*). Being seemingly more industrious than student A10, she put more time and effort into her studies. On Monday, she wrote: “I finished my essay successfully after revising it for many times. I’m looking forward to my next challenges.” Her motivation dipped a bit on Tuesday as she felt that she was not getting as much from her EAP class as she hoped for: “I think my EAP class a little boring cause I feel it not so efficiency.” Later, however, her motivation increased because of positive experiences, including the opportunity to use English outside of class when she met some international students. “This was the first time I was brave enough to talk with the international students who I totally didn’t know. Anyway, I felt great, shining and brilliant.” This experience greatly influenced her motivation and helped her to envision her future self: “I can imagine what I want to be.”

The two examples cited above suggest the importance that external factors outside of the language classroom have in shaping motivational disposition. Furthermore, they demonstrate how the push and pull of factors, both internal and external to the language learner, give rise to emergent and dynamic motivational dispositions.

Week 7 L2 Motivation Network

The network graph of Week 7 contained only 207 motivational factor nodes (see Figure 5). This may be explained by the fact that this week was the semester break and students likely did not feel the pressure to prepare for classes. However, it is also possible that their attention was more focused on the tasks they had to complete (e.g., encroaching mid-semester examinations) and other extraneous factors were not accounted for. There were only seven clusters in Week 7, with the same major clusters still driving the motivational system: Assignments and assessment holding 25.94%, Physical health 9.77%, and Being and feeling 28.57% of the nodes.

The positions of the two students are different in Week 7 than in Week 3. Student A10 has shifted slightly closer to Assignments and assessment. “Prepare for exam again,” he wrote on Monday. Yet, he felt that this week was for rest: “My vacation is come!!!!,” and although he did some studying, this was not very enthusiastically done. “Don’t want to study (oh my god!!!),” he admitted, which explains his average motivational level of 1 (*slightly demotivated*) for the week, with values dipping down to 0 – *completely demotivated* on Monday, Friday, and Saturday. Although the student was aware that effort should be expended to prepare for an upcoming exam, this awareness was not enough to counteract the influence that the student’s desire to rest had on his motivational disposition.

The location of student C3 moved from being between Physical health and Good desires in Week 3 to being in the proximity of the major cluster of Being and feeling and nodes representing negative factors, such as Being unprepared, Time was limited and Can’t progress in Week 7. Although she is still linked to nodes within the Good desires cluster, during this week she exhibited a demotivated disposition. “I finished my mid-term exam today. I went out with my friend and came back very late, so tired to learn EAP.” Although she was studying on other days, she took a long weekend holiday (Friday–Sunday) with her mother: “I went to Nanjing for a holiday with my mom. I don’t want to think about the study issue very often during these days.” These factors had an impact on her motivation which was an average of 2 (*slightly motivated*) this week.

Figure 4. *OpenOrd Layout of Week 3 With Prominent Clusters Labelled*

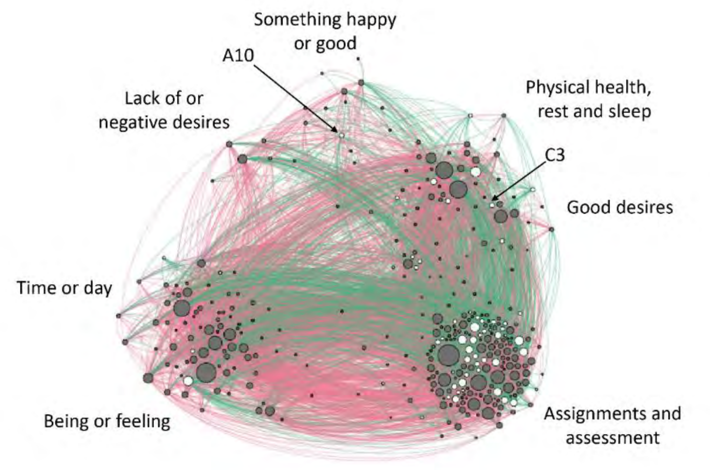


Figure 5. *Week 7 OpenOrd Layout With Prominent Clusters Labelled*

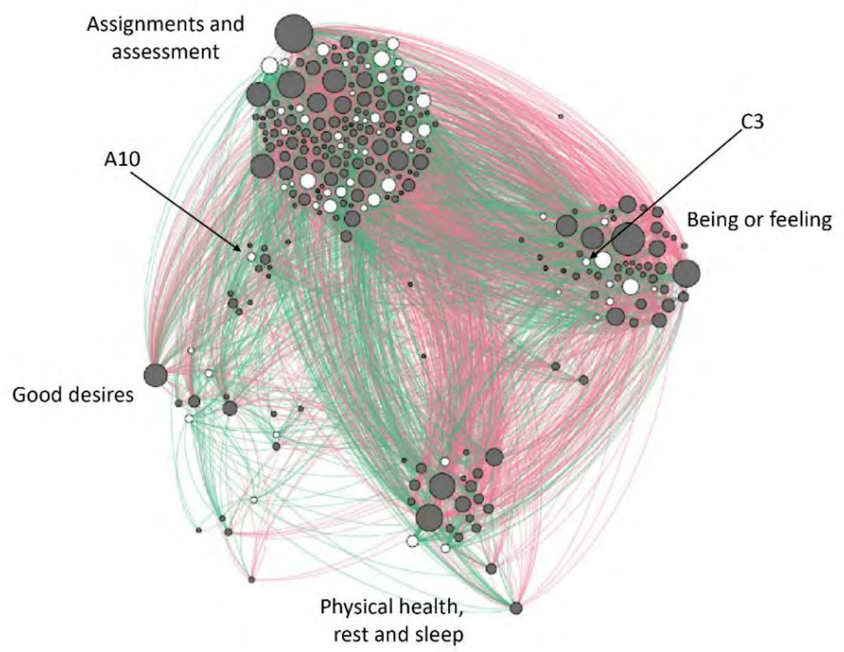


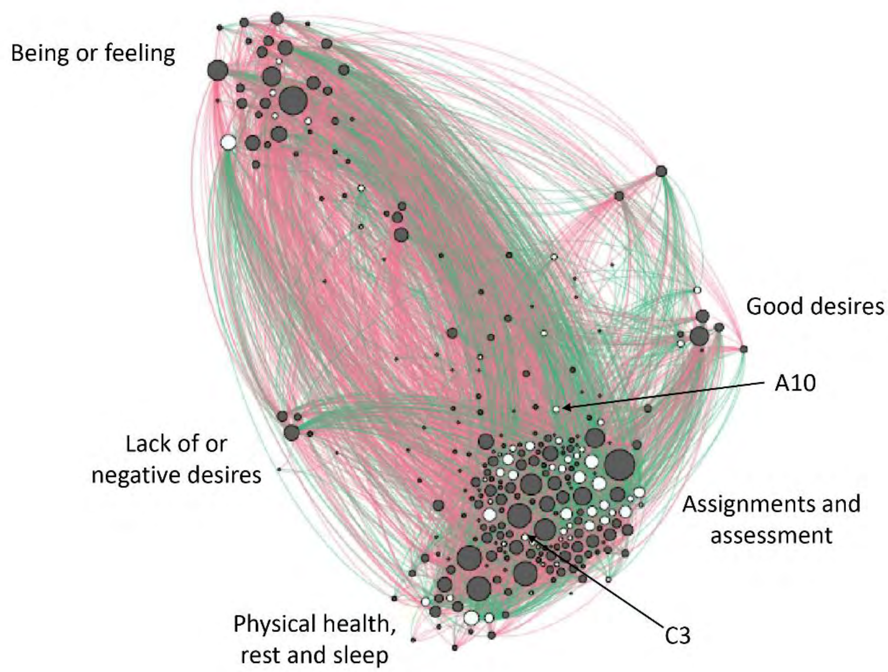
Table 3. *Comparison of Node Sizes (% of Total Nodes) of Selected Clusters in Week 3, Week 7, and Week 9*

Cluster	Week 3	Week 7	Week 9
Assignments and assessment	22.08	25.94	18.25
Physical health	13.1	9.77	10.95
Feeling or being	19.09	28.57	24.82

Week 9 L2 Motivation Network

The network graph of Week 9 was composed of 215 motivational factor nodes (see Figure 6). This week's network shows a different picture than the previously discussed weeks in which students had impending assignment deadlines. While assignments and assessments generally motivated the learners, health issues arising from lack of sleep, tiredness, and stress, had a negative impact on their motivation. In Figure 6, Assignments and assessments and Physical health are very closely connected to each other while in the previous weeks they were connected, but more distinctly separate. Furthermore, although the main motivational clusters are still present in the network, their balance has slightly changed (see Table 3). Assignments and assessment now holds 18.25%, Physical health 10.95%, and Being or feeling 24.82% of the motivational factor nodes.

Figure 6. *Week 9 OpenOrd Layout With Prominent Clusters Labelled*



As the network's structure changes, so too do the positions of students, as demonstrated by students A10 and C3 (see Figure 6). In Week 9, both students are pulled much closer to the Assignments and assessment cluster. Student A10's motivation was fluctuating wildly during this week, almost on a daily basis, from 0 – *very demotivated* to 3 – *fairly motivated*, with an average motivation level of 1.28 (between *fairly demotivated* and *slightly motivated*) for the week. One important reason for A10's low motivation was that his lecturer cancelled class in order to attend a conference. This, in combination with general tiredness (e.g., "Didn't sleep well and feel tired"), and a negative attitude towards preparing for exams (e.g., "do some works ... and I don't like to do it") adversely affected his motivation. He would have liked to spend his time differently, as he noted on Wednesday: "I want to play computer games with my friends." What student A10 demonstrates is that while a student node in a NA graph may be in close proximity to a major cluster (due to the number of times the student refers to factors that comprise the cluster), the parent factor representing the major cluster may not actually exert enough influence to result in substantial change in the students' motivation. In other words, while A10 frequently cited assignments and assessment as important factors, they ultimately failed to push the student's motivational disposition to sustained positive levels.

Student C3 did not enter anything in her motivation journal for three days (Monday–Wednesday), perhaps because of stress from looming assessments or research fatigue. However, for the rest of the week she reported a very high level of motivation, an average of 3.5 for the rest of the week. Her motivation was driven by a desire to get a good grade: "Speaking exam is coming and I think I need to prepare well and sufficient" (Thursday). On Friday, she attended a communication-support workshop where the teacher was "nice and gentle which encourages me a lot," which boosted her motivation.

The data from the analysis of these three weeks therefore suggest that although the general structure (i.e., major communities) of the L2 motivational network remained more or less the same, there are changes in the strength of these prominent motivational factors. Additionally, our analysis indicates that motivational factor nodes can fade into and out of the network as they connect, disconnect, and reconnect to other motivational factors and learners. The network graphs provide a visual representation of how particular arrangements of motivational factors at varying times move learners' nodes into different positions of centrality and levels of connectivity, thereby pushing and pulling on students' motivation, nudging it towards more motivated or demotivated attractor states.

Central Relational Links in the Network

Multiple means were leveraged to identify central relational links within the L2 motivational system. First, the weight of the edges between motivational factor nodes (i.e., how many times two nodes are connected to each other or how strongly these nodes are linked together), was explored. Our data indicate that there are 9,957 edges among the 1,048 motivational factor and student nodes. Yet, the vast majority of edges (6,714) in the network have an edge weight of one, which means that the link between two nodes (either between motivational factor and student node, or among motivational factor nodes) only appears once.

99.55% of all the network connections have an edge weight of five or less. This suggests that these particular links do not play central roles in the network, given their relatively weak connections between nodes. The strongest links are between motivational factors that belong in the same cluster of nodes (i.e., a group of nodes that function in the network in a similar manner and often, but not always, relate thematically), rather than linking different clusters of the motivational system together. In other words, while edge weight may assist in identifying important links within a particular cluster, it proves less useful in identifying central relational links in the L2 motivation factor network as it cannot adequately explain the push and pull of connections between different clusters that ultimately steer the network towards or away from particular attractor states.

A second and likely more fruitful way to identify central relational links within the network is to examine specific motivational factor nodes that act as hubs that bridge not only individual nodes with each other, but also amongst clusters. Betweenness centrality statistics, which provide insights into the central relational roles that nodes play within a network, were used to identify nodes that serve as central relational links (see Table 4). Visual representations of these nodes and their connections to each other are provided (see Figure 7 for Weeks 3, 7, and 9, respectively). These values and graphs highlight the importance of assignments, being and feeling, good desires, physical health, classes, and even the particular time of day or day of the week as prominent factors that play central relational roles as they connect various clusters together; they serve as synapses that allow feedback to move about the system as various motivation factors push and pull on connections both within and across clusters.

To explore the degree to which these motivation factors change in their roles as central relational links, the standard deviation of these nodes' betweenness centrality statistics for Weeks 1–10 were calculated (see Table 5). Despite being the node that exhibited the greatest amount of fluctuation in its betweenness centrality values over the 10 weeks, Assignments was the node with the highest betweenness centrality value for each particular week.

This means that the L2 motivation network is primarily controlled by Assignments although its overall influence on other network elements may change on a weekly basis. Similarly, while Being or feeling had the second greatest standard deviation of betweenness centrality values, it always came second for each individual week. While showing less fluctuation in overall betweenness centrality values across the 10 weeks, the remaining nodes exhibited more change in their ordering as they traded places with each other in the list of nodes with the highest betweenness centrality values for each week. Exams and tests, for example, became more prominent towards the end of the 10 weeks as students began to prepare for this form of assessment. This change in the rank of motivational factors demonstrates the dynamic changes within the network and may also account for the varying strength of motivational forces that move the system closer to more motivated or demotivated attractor states. In short, Assignments and Being or feeling were the two nodes that consistently played the greatest role in connecting various nodes across the network although their strength may have changed weekly.

Table 4. *Nodes With the Highest Betweenness Centrality Values in Weeks 3, 7, and 9*

Week 3	Week 7	Week 9
Assignments (7910.82)	Assignments (5506.52)	Assignments (4700.31)
Being or feeling (6168.59)	Being or feeling (2977.38)	Being or feeling (2996.33)
Time or days (4130.65)	Time or days 1900.93)	Exams, tests (1984.45)
Physical health (3334.44)	Desires (good) (1354.34)	Physical health (1617.77)
Rest and sleep (2826.93)	Exams, tests (1290.71)	Time or days (1587.98)
Desires (good) (2434.22)	Feedback (1196.70)	Desires (good) (1487.80)
Classes (2319.30)	Physical health (1101.18)	Rest and sleep (1444.25)
Busy (1959.87)	Classes (1071.00)	Desires (lack of; negative) (1385.28)
Exams, tests (1786.81)	Deadline (946.89)	Classes (1224.18)
Negative (1664.10)	Rest and sleep (879.36)	D14 (949.07)

Figure 7. *Top 10 Central Relational Nodes of the Network for Weeks 3, 7, and 9*

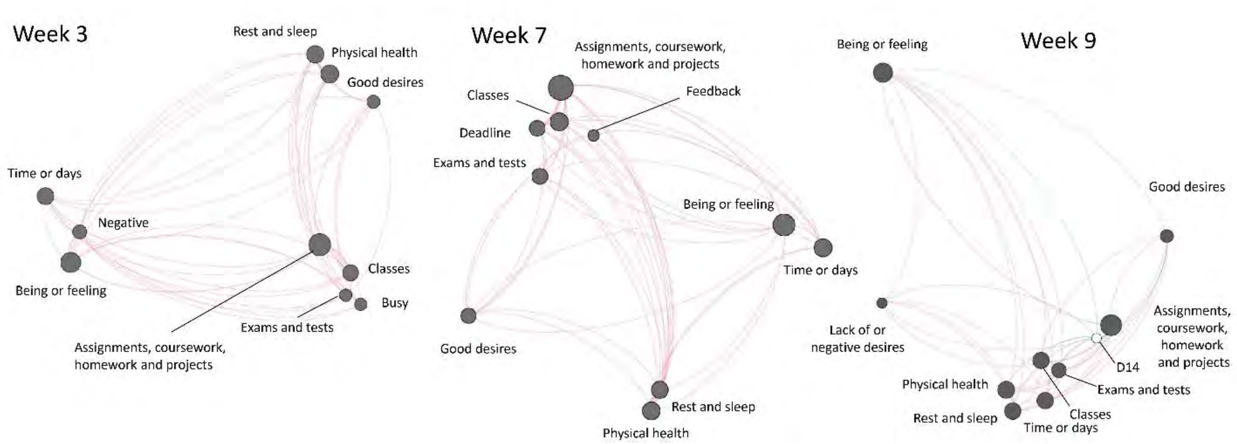


Table 5. *Standard Deviation of Betweenness Centrality Statistics for Nodes That Serve as Central Relational Links in Weeks 1–10*

Nodes	***SD***
Assignments, coursework, homework, and projects	28214.73
Being or feeling (moods and emotions)	19775.94
Time or days	10516.78
Classes	9709.00
Physical health	7962.73
Desires (good)	7320.47
Exams or tests or quizzes or assessment	6562.27
Rest and sleep	6424.16
Busy	5370.90
Negative Emotions	4731.39

DISCUSSION AND CONCLUSION

Understanding how central relational links within the CDS of L2 motivation affect emergent motivational dispositions, and conceptualizing the dynamic and diachronic nature of language learners' experiences have been raised as key enterprises to undertake in the field of L2 motivation (Al-Hoorie et al., 2021; Hiver & Papi, 2019). This study has taken important steps in these endeavors by leveraging NA to explore if and how central relational links' operations within an L2 motivation network change over a period of 10 weeks.

We found that the composition of the motivational system dynamically changed from week to week. This is made evident by the fact that not all factors reported over the 10 weeks appear in all weeks, the combination of factors changes each week, and the degree to which factors play a central role in shaping the trajectory of the network exhibit variation over time.

Two avenues to exploring the central relational links within the network were pursued. The first was investigating the weight of the edges between motivational factor nodes. It was found that edge weights, while effective for identifying connections between nodes within the same cluster, proved ineffective in illuminating the macro dynamics of the system (i.e., how different clusters of factors pushed and pulled on each other to steer the direction of the emergent motivational disposition of the learners). The second method, betweenness centrality statistics, proved more effective in highlighting the motivational factors that play the role of central relational links within the system. While Hiver and Papi (2019) have pointed out the need to explore the "central relational links in operation that can offer insight into the workings of the [motivational] system and inform actual adjustments that need to be made" (p. 130), no explanation of what these central relational links might look like is offered. Based on the findings of the current study, we suggest that relational links of motivational factors in NA are best understood as nodes with high betweenness centrality values, and not edges, which is in line with what general NA research suggests.

As noted by Barabási, nodes that may be initially considered relatively unimportant, can actually have a significant influence on how a network operates, if they act as a bridge through which other nodes can communicate (Science & Cocktails, 2016). In an example, he cites research that aimed to map out the communication patterns of a Hungarian company, which was concerned that information was not being communicated effectively within the organization. NA analysis revealed that none of the top- or even mid-management, who were generally responsible to communicate directives to other employees, acted as hubs in the company network. One lower-level employee, however, acted as the most connected person and the predominant source of information: the individual responsible for workplace safety. He was a talkative individual whose role involved visiting every department in the company; he picked up information in one department and dropped it at another one. People were attentive to the information he shared and thus he, without holding a management position, had become one of the most influential employees in the company in regards to effecting change in the organization by enabling communication between departments.

This example illustrates how hubs play a significant role as central relational links in that they enable the flow of information throughout the network. However, they may not necessarily be the nodes that are primarily responsible for influencing the trajectory of an L2 motivation network towards a desired state. Liu et al. (2011) claim that such a role is played by 'driver nodes;' the manipulation of the input these nodes receive may afford a degree of control over the trajectory of the network. They also found, counterintuitively, that the "driver nodes tend to avoid the high-degree nodes" (p. 167). In our data, the central relational nodes act as hubs, and therefore, they have a high degree. This means, if Liu et al. (2011) are correct, that although these motivational factor nodes are important to maintain the integrity of the motivational CDS and prevent it to reach equilibrium (i.e., an either ultimately motivated or demotivated state), they may not be responsible for setting the course and direction of the system. Yet, it remains to be seen if the concept of driver nodes is applicable to the L2 motivational system.

What can be concluded from the current study is that the motivational factors of Assignments, Coursework, Homework, and projects, Being and feeling (moods and emotions), and Physical health played central roles in connecting nodes and providing structure between communities of factors within the motivational system, which was echoed in Kiss and Pack's (2022) findings. The findings of the current study, however, highlight the stable, and at the same time, dynamic nature of these motivational factors. These central relational links are dynamic, in the sense that their betweenness centrality statistics can change significantly over time, and yet they are stable in their role as central relational links, as made evident by the fact that they remained at the forefront of nodes with high betweenness centrality values throughout the 10 weeks.

When evaluating the implications of such findings, it is important to consider the generalizability of findings given the diversity of educational, cultural, and personal contexts. Although our data suggest that motivational CDSs of students that share a particular educational and sociocultural context are similar, there are individual differences in their trajectories. In a similar research vein, Papi and Hiver's (2020) conclusions are similar. They managed to identify factors that influenced their Iranian post-graduate participants' motivation in similar ways, and, although individual variations were present, the learners' motivational trajectories showed similarities as they were influenced by factors they all experienced. Yet, Papi and Hiver do warn that "individuals may not reflect all characteristics of the group and the group may not be equally representative of each individual's developmental trajectory in time and space" (p. 227). Their research, however, looked at a rather limited spectrum of the motivational CDS and equated the system with the individual. We suggest that CDS-informed research on motivation should employ a broader lens, as was exemplified by our own research.

Our findings also suggest that while individual variations in L2 learner motivation are undoubtedly observable in the network, (e.g., the different motivational trajectories of students A10 and C3), central relational nodes remained stable in their roles, thereby giving the system a certain level of predictability. While other motivational factors appear, disappear, and reappear, as their connections and strength of connections change over time, central relational nodes give shape to the structure of the motivational system. This indicates that although L2 motivation is a CDS, the shared sociocultural and educational experiences may provide a particular structure which allows order to emerge. Therefore, based on the findings of the current study that the same central relational nodes are present in the individual motivational systems of most learners, we suggest that L2 motivation is somewhat predictable in shared sociocultural and educational contexts. This may allow educators to gauge what motivational factors play significant central relational links within the motivation network of their learners.

This is further supported by the finding that, based on network statistics, the NA software grouped students into clusters (see Table 1) that mostly matched their classroom groups; this clustering was not intentionally orchestrated by the researchers. Since the network was not created to indicate any links between students, the clustering suggests that the shared context within a particular tutorial group had an impact on what factors motivated them. Our data show that most students (70.58%) in Group D were connected to the Assignments, coursework, homework, and projects and most students (80.95%) in Group D were linked to the Good desires cluster. Whether this happened because students talked to each other about what motivates them, shared their broader life experiences with each other, and/or because they simply experienced the same lessons delivered by the same teacher, it is difficult to say; it is simply beyond the scope of this investigation to establish the reason for such clustering phenomenon. We propose that NA be used in future research to explore to what degree central relational links differ according to sociocultural and educational contexts.

Lastly, the current research has confirmed Hiver and Papi's (2019) hypothesis that "there are likely to be a handful of central relational links in operation" (p. 130) in the L2 motivation CDS. We have demonstrated that in regards to NA, nodes, not edges, serve as central relational links that connect different parts of the system together and allow clusters of motivational factors to interact with each other. These central relational nodes (or motivational factors) are both stable and dynamic, provide the structure for the system, and allow the emergence of certain motivational dispositions. While this discovery warrants more research and data to be validated, this does not hold us back to consider what direction future research employing NA and CDST should take. One possible avenue could be based on the fact that certain motivational factors can exert both positive and negative influence on learner motivation (Pack et al., 2021). We suggest that future research focus on identifying driver nodes (Liu et al., 2011) which primarily exert a positive motivational force, and thus, have the potential to move the motivation system toward a more motivated state. Influencing such nodes would likely prove useful for teachers in helping improve their learners' motivation to put effort into learning an L2.

Authors' Contributions

T.K. and A.P. contributed to the research design, data collection, data analysis, and the writing of the manuscript.

Ethics Approval & Consent to Participate

This study was conducted at Xi'an Jiaotong–Liverpool University. The study was approved by the University Ethics Committee (proposal number 19-02-28).

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