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Mapping Cognition and Performance for Digital Evaluation in Higher Foreign Language Education: A Whole Network Model

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Abstract. In the wake of the digital transformation of foreign language education, there would be inevitable transformation and reconstruction in educational evaluation modality. While the embedding of educational data mining technologies and Learning Analytics have already become the emblem of digital evaluation, very few relevant studies provide workable data processing and analysis models for higher foreign language education. In this context, this research aims to propose a software-aided data processing, analysis and visualization model for the empirical data sets acquired from actual blended teaching practice. This research was conducted in an application-oriented university with a small-scale sample of 20 English major juniors. Theoretically, the research design is framed by learning analytics; Methodologically, this research is designed as a mixed-method and adopts the social network analysis paradigm in data analysis. The contribution of the research is a practical empirical approach to digital evaluation and the development of a whole-network-based mapping model which produces the cognitive ability and performative map of learners for the evaluation of learner's language and socio-cognitive development. The research findings suggest a whole network analysis paradigm can be integrated with digital evaluation in areas like multidimensional data synthesis, analysis and visualization, and the software-aided whole network analysis can be a surrogate measure for digital evaluation.

Keywords. Whole network analysis; cognitive and performative mapping; digital evaluation; higher foreign language education

1. Introduction

Nowadays, echoing the mainstream trend of digital transformation in education, cutting-edge digital technologies like GAI (Generative Artificial Intelligence), advanced computing, digital twin, blockchain and metaverse gradually become the enablers of digitalized and smart foreign language teaching and learning. The ever-accelerating integration of the above-mentioned digital technologies and higher foreign language education brings about education evaluation reform in universities and colleges. The

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constant rising of new evaluation techniques such as computer-aided testing, AI intelligence evaluation, and holistic intelligent evaluation forecasts the coming of a digital and intelligent evaluation era, however, these techniques have not been practically adapted to different application scenarios such as blended teaching and learning. Besides, in the field of higher foreign language education, the development and utilization of evaluation tools can not keep pace with the demand of up-to-date evaluation paradigms such as online feedback, platform-based peer evaluation, computer generated feedback and data mining automated feedback in cloud evaluation.

Apart from the technological inaccessibility, many foreign language teachers at universities and colleges only have a vague concept of the imminent intelligentization and digitalization in evaluation reform. Substitute e-assessment methods like portfolios, podcasts, storytelling, checklists, rubrics, surveys, student-centered assessments, and reflections[1] are still categorized as digital evaluation, and even the use of such e-assessment methods and strategies is limited to individual teacher proactivity.

In response to the above issues, this research aims to distinguish e-assessment from digital evaluation because digital evaluation requires the comprehensive and learner-oriented institutional design, planning, and implementation, as well as data-driven learner profiling. Technically, this research addresses the problem of detecting, identifying and analyzing, especially interpreting the multi-modal cognitive and performative data generated in blended teaching and learning by building evaluation index matrices and cognitive and performative whole networks.

Structurally, this research first expounds the significance of measuring cognition and performance in digital evaluation, then explores the theoretical feasibility of building a whole network model for cognition and performance in blended teaching and learning. Finally, the detailed mapping procedures are presented to examine the evidence of learners' language development and soci-cognitive development.

2. Literature Review

2.1 The Assessment of Cognition and Performance in SLA

A systematic literature review was conducted to provide a comprehensive understanding of existing assessment paradigms of cognition and performance in SLA. The review uses Google Scholar web search engine to access articles and literature related to the assessment of cognition and performance in foreign language teaching, using keyword screening for selection.

In the field of SLA, the assessment of learner's language knowledge and aptitude is largely concerned with describing and explaining learner's language development. Relevant researches largely center on the cognitive processes involved in the execution of language skills and strategic behavior in simulated testing and non-testing contexts[2]. Dual-task methodology, self-ratings, and expert judgments are the up-to-date paradigms used in assessing task-generated cognitive demands for teachers to manipulate task complexity[3].

With the help of state-of-art AI technologies and advanced computational model, the assessment of cognition in SLA takes the lead in intelligentization and digitalization. The cognitive abilities behind specific acquisitional process such as orthography acquisition can be simulated and evaluated using multi-layer perceptron neural network-gray wolf optimizer computational model[4].

Teachers may use techniques such as virtual reality (VR) to simulate real-life language contexts to assess learners' communicative abilities in immersive environments or natural language processing algorithms to evaluate learners' naturalistic performance and provide detailed feedback on linguistic accuracy and proficiency levels. For example, computational linguistic analysis such as the artificial neural network (ANN)-based computational model can be applied to analyze learners' written or spoken language data, predict factors affecting learners' overall English competences, locating abnormality in learning by reviewing learners' individualized ANN trajectories[5].

Socio-cultural theories of learning suggest language development is intertwined with socio-cognitive development, therefore, student-centeredness and authenticity are central to the validity of existing language assessment method. There is an emerging emphasis on authentic assessments and performance evaluation which are incorporated with genuine tasks and activities in real-life scenarios.

In their research, Roderick A. Farmer and Baden Hughes proposed the CASE (Cognition, Activity, Social Organization and Environment) framework for the evaluation of learner-computer interaction in computer-assisted language learning and explored its application to computer-assisted language learning software development[6].

In the assessment of learner's real performance, there is a tendency towards multimodal assessment in which multiple modes of communication (e.g., speech, gesture, writing) will be integrated to capture the complexity of language use and assess learners' communicative competence comprehensively. In this regard, e-portfolios such as EPOSTL(European Portfolio for Student Teachers of Languages) have proven to be an effective digital self-assessment tool for developing students' metacognitive strategies, eliciting their self-regulated monitoring and reflection on their experiences, performance and progress in the course of foreign language education[7][8].

Apart from e-portfolios, digital games and interactive platforms like Blackboard Collaborate have been used as the learning management system for collecting data on learners' online linguistic performance and problem-solving strategies[9].

With the development of the above digital tools for performative assessment, new research initiatives aim to reform the traditional language testing paradigm with digital formative assessments containing rubrics for evaluating fluency, accuracy, grammatical structure, pronunciation, and vocabulary, and structured interviews for grading learners' actual performance in both test types[10].

Existing literature suggests the need for cognitive and performative assessment methods has heightened over the past decade, digital tools, artificial intelligence applications, scaffolding and feedback loops have been incorporated into assessment tasks to gauge learner's potential for language development, achievement, motivation and identify areas for intervention on the basis of project-based teaching approach in foreign language course[11].

This research is actually inspired by Olesya Dmitrievna Medvedeva et al's innovative research. In their blended teaching practice, they defined learners' soft skills and put forward three types of interactive problem-based tasks and assessment criteria for corresponding evaluation, which allow the teacher to monitor the progress of soft skills such as problem solving, teamwork, leadership, time management, technology skills, and analytical and creative thinking. The most intriguing part of their research is the utilization of online educational platform as data sources and the visualization of performative assessment results.[12]

Obviously, the aforementioned digital tools and platforms are generally used for data collection in the assessment of cognition and performance in SLA. While the cognitive, performative, psychological, instructional, and task developmental aspects of assessment have been investigated, few analytic methods and tools have been proposed for data processing and visualization. Therefore, this research intends to explore the empirical validity of Olesya Dmitrievna Medvedeva et al's evaluation framework and enrich it with a unique cognitive and performative mapping tool for learning analytics.

2.2 Social Network Analysis and Digital Evaluation

From the sociotechnical perspective, digital assessment is the implementation of digital tools like computer, web, online learning platform in the evaluation of learners' e-learning or blended learning outcome. The most common formats of digital assessment in higher foreign language education are quizzes, virtual simulations, peer and teacher assessment, automated and self-assessment, digital game-based assessments, e-Portfolios, e-activities etc.[13]. Technically, the execution of digital assessment requires carefully-designed assessment tasks such as creative writing, translation tasks, essays, oral presentations, project-based cases, games and simulations, or even discussion entries, diagram exercises [14].

Broadly speaking, digital evaluation is case-oriented, drawing cognitive diagnostic conclusions from individualized performative data derived from the statistics module of online platforms and learning management systems (LMSs). In a sense, the concept of digital evaluation is inseparable from the application of e-assessment tools. However, the up-to-date literature suggests thinking tools such as learning analytics and social network analysis (SNA) can be used to evaluate the implementation of e-assessment.

Recently, in the field of education, SNA and Bayesian Network Analysis have been used as data mining and analytic methods in sustainable computer-based formative assessment system to generate evidence-centered design (ECD) and analyze learners' performances based on a computational psychometric framework[15]. Through evidence-centered design, SNA or Epistemic Network Analysis can be used to measure "thinking and learning in action"[16].

In digital evaluation, SNA may assist teachers in constructing perceptual models and evaluation rubrics to enact ECD and promote students' sociability. Currently, SNA methods such as MDS, Matrix Algebra and Cluster Analysis have proven extremely powerful in analyzing student relationship network. With mathematical and graphic representations of peer team coordination and communication patterns, group and class dynamics, SNA help teachers solve potential social problems and promote students' participation.

Other frontier research domains in the field include the structural and functional analysis of the professional networks of educators as inquirer, collaborator, counsellor and weak socializer[17], curriculum design, knowledge construction and learning network analysis[18], the identification and analysis of interaction, cooperation and participation patterns in real and virtual learning community[19][20]. Similarly, SNA has also been used in the analysis of the supply-side of learning such as the social support from family, school and community.

As far as the current research is concerned, the most intriguing research orientation in SNA is the construction of diagnostic learning and social network for the improvement of curriculum design and comprehensive quality evaluation, which accurately and scientifically profiles the complexes of learners' relationship, information flow and learning environment.

Actually, SNA might have an unexplored value in the study of learners' performance in technology-enhanced learning at large and in blended learning scenarios in particular. In blended teaching, SNA can be used to study students' positions in information exchange networks, communicational activities, and interactions, to help teachers monitor and understand each participant role and learn how interactions can affect academic performance[21].

In this research, cognition and performance are foregrounded as dynamic evaluation dimensions connected via a whole network and whole network analysis (WNA) of SNA is used as the visual and mathematical technique to map learners' cognitive and performance trajectory in blended learning and help the author generate meaningful interpretation of cognitive and performative data acquired in blended teaching.

3. Research Hypothesis

As social actors in a technology-rich learning environment, every learners' performance maybe cognition-oriented. So, cognition and performance are in an asymmetrical, dynamic and temporal relationship, constituting the whole network in SNA.

In a Social Network, the whole network denotes the multiple ties between social actors (Friend Network) or organizations (Organizational Network). Since the coordination of brain's complex neural network determines the working of the cognitive mechanism underlying language aptitude, this research attempts to model language-specific cognition through a whole network whose structure and function are modulated by performance. Performance is not only conducive to learning and experience but also beneficial to the plasticity of the neural network.

To fully reveal the reciprocity and transitivity between cognition and performance, this research constructs cognitive and performative matrices which are comprised of cognitive and performative evaluation indexes or rubrics and the corresponding achievement level designated by different assigned value.

Accordingly, the research paradigm is based on the following hypotheses:

H1: The cognitive evaluation indexes constitute a whole network that mirrors the neural network of the brain.

H2: The performative evaluation indexes constitute a whole network representing an individual's learning engagement and participation.

H3: Density of an individual's cognitive network is positively associated with the working and coordination of aptitude-related cognitive abilities.

H4: Density of an individual's performative network is positively associated with the structure and quality of the learning network and social network.

H5: Density of an individual's cognitive network is positively associated with the density of an individual's performative network.

4. Research Methodology

Cognitively, this research aims to map patterns of information acquisition, processing, and knowledge construction in independent inquiry learning. Performatively, this research aims to map patterns of interaction and communication in collaborative learning and communicational activities.

Therefore, the entire research design is guided by learning analytics and the research was conducted in three stages. First, the cognitive and performative evaluation index systems were set up for data collection. Then, the cognitive and performative assessment tasks were devised in accordance with the cognitive and performative indexes and the empirical data was collected. Finally, the research constructed the adjacency and Q matrices for learners' cognition and performance and used whole network analysis, a paradigm of social network analysis (SNA), to generate the cognitive and performative whole network for teachers and learners respectively. The last procedure is to compare the density, degree and centrality of the two networks, using software tools like UCINET to measure the gap between teachers' model and learners' model and evaluate learner's language-specific cognitive ability and the actual performance. In the due course, the graphical representations of the cognitive and performative whole network were generated via NETDRAW.

4.1. Data Collection

The data collected for cognitive and performative evaluation mainly comes from two sources, the language aptitude test score and the values of relevant formative evaluation indexes. The online language testing platform adopted in this research is UDIG for higher education developed by Foreign Language Teaching and Research Press. The diagnostic language testing system includes reading, listening, speaking, vocabulary, grammar, and writing tests embodying measurable micro-skills that constitute language aptitude, as is described in China's Standards of English Language Ability. After each test, the platform generates a visualized report of the test results for each class. The author selected one class of English majors for grammar and reading tests and integrated learners' test scores with the corresponding values of formative evaluation indexes.

4.2. Data Integration and Feature Extraction

The learners' language testing scores and formative evaluation index scores are extracted from the online learning platform and are assembled in one Excel chart, as is shown in Table 1:

Table 1. Formative evaluation indexes

Student Number	Level 4-reading score	Grammar Score	Task Point Learning"	Learning Frequency	Online Discussion"	Posting
1	72	144	99.5	100	100	122
2	68	159	100	100	100	288
3	60	81	99.5	100	100	166
4	40	175	99.5	100	100	181
5	36	107	99.5	100	46	42
6	32	85	99.5	100	100	232
7	28	89	99.5	100	100	214
8	24	114	99.5	100	73	51
9	24	130	99.5	100	82	116
10	24	96	93.5	100	100	256
11	20	122	99.5	100	100	100
12	20	74	62.5	100	100	124
13	20	31	99.5	100	95	55
14	20	84	76	100	57	95

15	20	23	99.5	100	100	104
16	16	46	93.5	100	100	77
17	16	66	99.5	100	58	85
18	12	107	99.5	100	100	93
19	12	100	99.5	100	100	143
20	12	115	100	100	100	266

Student Number	Online Homework	Online Test	Online Interaction	Presentation	PBL Project	Final Examination Score
1	45	89	100	59.6	59.6	56
2	46	90	100	59.6	59.6	81
3	44.47	91	94	59.6	59.6	79
4	46	87	100	59	59	83
5	45	93	20	60	60	68
6	0	90	100	59.2	59.2	77
7	43	88	100	59	59	73
8	0	88	38	59	59	72
9	44	85	78	40	40	74
10	44.47	93	100	59.6	59.6	74
11	42.53	89	68	59.6	59.6	71
12	42.53	91	100	39.6	39.6	66
13	44	82	18	58.6	58.6	47
14	43	88	60	59.6	59.6	72
15	0	84	46	59	59	79
16	40	82	22	60	60	72
17	0	90	52	58.6	58.6	72
18	40	87	8	59.6	59.6	62
19	46	89	62	59	59	68
20	45.53	90	100	59.2	59.2	83

The author then assigned all formative indexes into the cognitive and performative sets. The cognitive sets are indexes for learners' language aptitude and achievement, including level-4 reading scores, grammar scores, online homework scores, online test scores, and final examination scores. The performative sets are indexes for learning engagement, which is embodied in assessment task scores like task point learning, learning frequency, online discussion, posting, online interaction, presentation, and PBL (Problem Based Learning) project.

5. Results

5.1. Mapping Cognition

- Generating Cognitive Indexes Framework

In line with research findings on normal language acquisition and learnability theory, the ability to acquire language is the result of activating innate cognitive mechanisms. Language acquisition recruits the encephalic regions and neural networks essential to the working of verbal processing mechanisms such as memory, attention, and perception. Socio-culturally, non-verbal processing mechanisms are also coactivated with verbal processing mechanisms through socialization, which pertain to task execution, social interaction, learning and problem-solving in general[22][23].

Accordingly, the author associates those verbal and nonverbal processing mechanisms with different cognitive elements fulfilling different functions in the completion of blended language learning tasks and language tests and generates the cognitive indexes framework, which is listed in Table 2.

Table 2: Cognitive indexes framework

Cognitive Mechanisms	Cognitive Elements	Functions
Executive functions	Response inhibition; Working memory updating; Task shifting	Attentional control and self-regulation Comparing different ideas and attitudes
Memory	Working Memory Episodic Memory Procedural Memory	Input processing and segmenting Information retrieval
Attention	Selective attention Sustained attention Multi-modal attention	Noticing and coming into focus; Achieving salience; Attentional flexibility; Inhibitory control; Attentional switching; Attentional expansion; Visual search; Attentional stability
Perceptual speed	Perceptual sensitivity Attention allocation Situational awareness Decision-making Neurotransmission	Input information processing and simultaneous verbalization Phonological and graphemic unit identification
Reasoning and Logical Thinking	Concept formation Judgement Deductive reasoning Inductive reasoning Hypothesis making and testing Understanding logical relations Logical problem solving Flexibility of thinking	Making references Maintaining discoursal coherence Understanding syntactic and thematic relations Identifying discoursal patterns Generalizing Refinement in information processing Logical expression Semantic and syntactic processing
Learning Strategies	Metacognitive strategies Cognitive strategies Social and Affective strategies	restructuring/integration Error avoidance Automatization Automatizing-Proceduralizing
Social Intelligence	Affective recognition Intention recognition Empathy Social problem-solving Interpersonal Skills Social flexibility	Complexification Handling feedback Seeking social support Coordination and cooperation Affective control and self-adjustment Questioning

- Building the Cognitive Matrix

According to Table 2, the cognitive covariates of language aptitude include execution functions, memory, attention, perceptual speed, reasoning and logical thinking, learning strategies, and social intelligence. These cognitive mechanisms consist of different cognitive elements with multiple functions. There are altogether 31 active cognitive elements accountable for learners' scores in language test and cognitive tasks. To provide a cognitive diagnosis of the poor score in reading and grammar tests, the whole array of 31 cognitive elements is assigned to different columns and rows in an adjacency matrix for a correlation analysis, and the binary value 0 or 1 is accorded to each intersection of the columns and rows to signal the existence of any correlation between different cognitive elements, hence, the cognitive matrix is generated.

Afterwards, the data recorded in the cognitive matrix is transferred into NETDRAW for visualization, and a whole network of all the cognitive elements constituting language aptitude is produced (Figure 1).

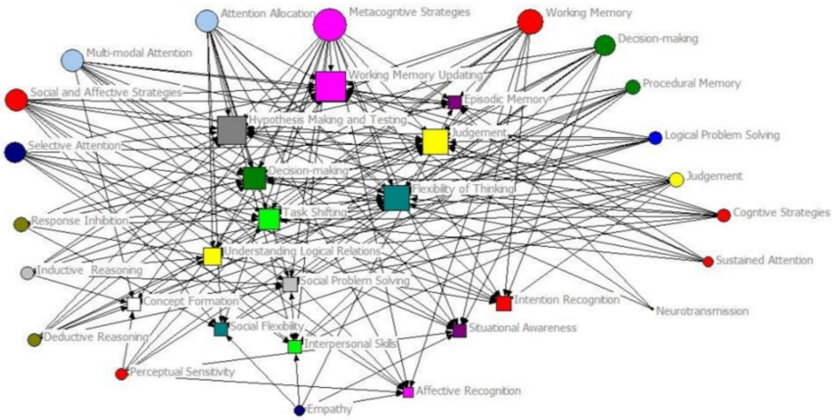

Figure 1. The whole network of cognitive matrix for learners

In the cognitive whole network in Figure 1, different cognitive elements are attribute variables represented as different nodes. The analysis of the whole network reveals the relationship between learners' attribute data. In this case, learners' attribute data is the different scores of online and offline language tests and cognitive tasks. The key notion in building the cognitive whole network is "degree." In a whole network, the nodes adjacent to one specific node are called that node's neighborhood, and the number of adjacent nodes is called node degree (also the degree of connection). As such, the degree of a node in a whole network is actually the measurement of the number of neighborhood and the graphic representation of the degree of a node is the number of lines connected to the node. [24]

As is shown in Figure 1, each node has lines coming to it or coming out of it (signaled with an arrowhead), which are termed the "in degree" and "out degree," respectively. Normally, "in degree" and "out degree" pertain to the node's centrality: having more lines coming to the node indicates the node is supported by another neighbor or at the higher-order end of the multi-lateral relationship. If the node denotes one cognitive element making up corresponding cognitive mechanism, the cognitive mechanism underpins more sophisticated and advanced language and socio-cognitive abilities. Similarly, having more lines coming out of a node entails the node supporting another neighbor, or at the lower order end, it is more basic and primary as a cognitive element. In Figure 1, the degree of different nodes is indicated by the size of corresponding squares or circles, which also corresponds to the node's centrality.

Based on different degrees and centrality, it is fairly clear in Figure 1 that more basic and primary cognitive elements such as selective attention, social affective strategies, multi-modal attention, attention allocation, and working memory support the more sophisticated and advanced cognitive elements such as working memory updating, hypothesis making and testing, decision making, task shifting, flexibility of thinking and judgment.

- Mapping Cognition Via Density

The rationale for building the cognitive ability map is to present diagnostic information on the multi-dimensional and fine-grained learner traits like the cognitive process and knowledge mastery, based on learners' response behavior and results in language tests and cognitive tasks. Therefore, this research adopts the Q matrix to bridge the observable response behavior and the unobservable cognitive traits manifested in the language test and cognitive task scores.

First, after building a whole network of cognitive indexes, the author correlates the cognitive sets in the previous formative indexes with relevant cognitive elements via the Q matrix shown in Table 3:

Table 3. Teacher's cognitive Q matrix

	Working Memory	Episodic Memory	Procedural Memory	Selective Attention	Sustained Attention	Multi-modal Attention	Perceptual Sensitivity	Attention Allocation	Situational Awareness	Decision-making
Level 4-reading score	1	1	1	1	1	0	0	1	0	1
grammar score	1	0	1	1	1	0	0	1	0	1
online homework	1	1	1	1	1	1	1	1	1	1
online test	1	1	1	1	1	1	1	1	1	1
final examination score	1	1	1	0	0	0	0	0	0	1

	Neurotransmission	Concept Formation	Judgement	Deductive Reasoning	Inductive Reasoning	Hypothesis Making and Testing	Understanding Logical Relations	Logical Problem Solving	Flexibility of Thinking
Level 4-reading score	0	0	1	1	1	1	1	1	1
grammar score	0	1	1	1	1	1	1	1	1
online homework	0	1	1	1	1	1	0	0	0
online test	0	1	1	1	1	1	0	0	0
final examination score	0	1	1	1	1	1	1	1	1

In the cognitive matrix, the rows are the cognitive indexes for diagnosis; the columns are the relevant items of formative evaluation suggestive of cognitive abilities, including the scores of level 4 reading, grammar test, online homework, online test, and final examination. Compared with traditional assessment methods, the current evaluation paradigm can be deemed as digital because it embraces the concept of data-driven and software-enabled cognitive diagnosis.

Still, it is the idealized expert's model or teacher's model of incidence matrix describing the relationship between the cognitive attributes and formative evaluation items. To make cognitive evaluation or diagnosis, a comparative analysis needs to be made of learner's model. Therefore, the author input each learner's actual score into the original intersection with the value "1" in the incidence matrix and get the learner's actual cognitive Q matrix, as is shown in Table 4:

Table 4. Learner's cognitive Q matrix

	Working Memory	Episodic Memory	Procedural Memory	Selective Attention	Sustained Attention	Multi-modal Attention	Perceptual Sensitivity	Attention Allocation	Situational Awareness	Decision-making
Level 4-reading score	0.12	0.12	0.12	0.12	0.12	0	0	0.12	0	0.12
grammar score	1.15	0	1.15	1.15	1.15	0	0	1.15	0	1.15
online homework	0.4553	0.4553	0.4553	0.4553	0.4553	0.4553	0.4553	0.4553	0.4553	0.4553
online test	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9	0.9
final examination score	0.83	0.83	0.83	0	0	0	0	0	0	0.83

	Neurotransmission	Concept Formation	Judgement	Deductive Reasoning	Inductive Reasoning	Hypothesis Making and Testing	Understanding Logical Relations	Logical Problem Solving	Flexibility of Thinking
Level 4-reading score	0	0	0.12	0.12	0.12	0.12	0.12	0.12	0.12
grammar score	0	1.15	1.15	1.15	1.15	1.15	1.15	1.15	1.15
online homework	0	0.4553	0.4553	0.4553	0.4553	0.4553	0	0	0
online test	0	0.9	0.9	0.9	0.9	0.9	0	0	0
final examination score	0	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.83

The crucial algorithmic step is to treat the actual score as numerator and divide it by the denominator, which is the original value 1 in the intersection. To attain algorithmic consistency, the original binary value 1 should be turned into the centesimal value 100 to reflect the actual attainment ratio of specific cognitive indexes.

Next, the author transfers learner's cognitive Q matrix into NETDRAW to generate the cognitive ability map, as is shown in Figure 2:

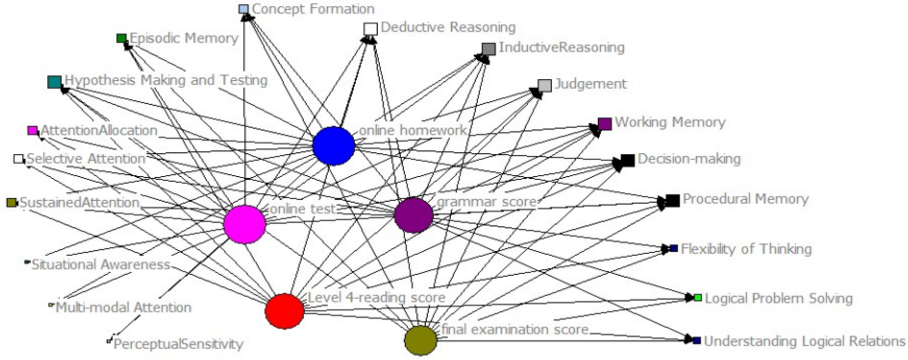

Figure 2. Learner's cognitive ability map

Again, the different sizes of the squares and circles signal different degrees and centrality of the nodes.

The notion of density is introduced from SNA to compare the teacher's model with the learner's model and measure the attainment gap. In SNA, density denotes the overall distribution of the lines as a measurement of its difference from the complete graph. In this research, the graphic representations of the teacher's model and the learner's model generated in NETDRAW are roughly the same, without visible distinction. So, the learner's attainment gap must be measured via the density calculation. In SNA, density refers to the closeness between the nodes and it is visibly embodied in the number of lines linking one node with others: the more the line, the larger the density. Generally, the larger the density of a whole network, the closer the relationship between network members, which means the whole network has an even greater impact on actors' attitudes and performance [25].

In a whole network of cognitive abilities, the larger density usually suggests the whole network provides learners with multiple cognitive resources or environments that enhance learners' performance. Comparably, lower density suggests the lack of coordination or connection between cognitive elements, which may lead to malfunction of cognitive abilities. Following this logic, the ratio between the density of teacher's model and that of learner's model can be used to measure learners' attainment gap in language-specific cognitive development.

Finally, the author inputs each learner's cognitive matrix with actual score values into UCINET to calculate the density of each learner's cognitive ability map, which is divided by the density of the teacher's cognitive ability map to get the attainment ratio, which is listed in Table 5:

Table 5: Learners' attainment ratio

Student Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Density	0.6	0.65	0.52	0.63	0.61	0.41	0.47	0.43	0.52	0.49	0.51	0.4	0.33	0.45	0.3	0.37	0.35	0.45	0.46	0.51
Attainment Ratio	0.82	0.88	0.71	0.86	0.83	0.56	0.64	0.59	0.71	0.66	0.69	0.6	0.45	0.61	0.4	0.51	0.48	0.62	0.63	0.69

The attainment ratio is of great diagnostic value because it designates the coordination quality of learners' different cognitive modules in contrast to the idealized expert model of the teacher. In the above figure, the attainment ratio below 0.6 is the salient indicator of impairment or malfunction in cognitive ability. It is up to the teacher to make further directed diagnoses according to different cognitive dimensions of formative evaluation items.

For example, to account for learners' poor scores in the level-4 reading test, it is necessary to identify the cognitive elements lacking or malfunctioning in completing the reading tasks. It is obvious in diagram 2 that a level-4 reading score correlates with the working of higher-order cognitive elements concerning logical reasoning, judgment, decision-making and problem-solving. The teacher then needs to correlate each test item with the tested knowledge points in the pregenerated knowledge graph to generate another Q matrix to determine the influence of malfunctioning cognitive elements on knowledge acquisition. Moreover, the teacher may perform the clique analysis to verify the relationship between the cognitive ability indexes and the relevant knowledge points. The teacher may even recommend the cognitive intervention strategies to learners and provide the prerequisite knowledge resources through a path analysis which predicts the acquisition of certain cognitive ability via the achievement of different knowledge points.

Regrettably, the correspondence between knowledge points and the tested items and language tests or cognitive tasks like level 4 reading hasn't been established, which leaves a blank area of building the knowledge-cognition map for future research.

5.2 Mapping Performance

- Generating Performative Indexes Framework

In the dimension of academic performance, this research draws primary data from online learning and interaction. Based on the collected data, this research examines learner's performance from three dimensions, namely, participation, engagement, and interaction, which are manifested in the indexes framework summarized in Table 6:

Table 6. Performative indexes framework

Evaluation Dimension	Formative Indexes	Formative Items
Participation	resource browsing, audio video learning	resource access; presentation PBL project; online discussion
Interaction	online punches, likes, posting and reviewing, random selection of participants, quick responder, rating, questionnaire survey, voting	Posting; online and offline interaction;
Engagement	task completion	task point learning; PBL project; online discussion

In the performative indexes framework, the formative indexes are applied to different formative items. There are altogether 7 formative items along the performative axis. Some of the formative items may overlap along different evaluation dimensions. For example, PBL project reflect a learner's degree of participation and engagement simultaneously.

In actual blended teaching practice, the scores of resource, task point learning, posting and online discussion can all be directly extracted from the Xue Yin online learning platform, whereas, the scores of presentation, offline interaction and discussion are derived from the teacher's grading and class observation, intra-group and inter-group evaluation. The teacher will add the scores to the score of online interaction through Chao Xing Xue Xi Tong learning app's scoring system immediately after the completion of each online interactive tasks such as random selection of participants, quick responder, rating, questionnaire survey, voting, and other offline interactive tasks such as panel discussion, brainstorming. Therefore, offline interaction and discussion are not distinguished as separate formative items, and the online and offline interaction scores are actually the overall course credits.

It must be emphasized that the PBL project includes group cooperative learning tasks, which generally take the form of background information retrieval and integration, group learning reports, role play, group reading and discussion, language games, translation practices, debate competition, survey reports, and independent learning tasks for individual learner's personal inquiry. Apart from information retrieval, digesting and application, independent learning tasks also include learning reflection, creative writing, language learning strategy analysis, comparative cultural analysis etc. The learning outcomes of PBL project include PPT, text-type learning report and reflection, as well as offline presentation. In this research, the scores of PBL project and presentation come from teacher grading and intra-group and inter-group peer rating, which are uploaded to the Xue Xi Tong app by the teacher into the corresponding rating module of the scoring system.

- Building the Performative Matrix

Just as the building of the cognitive ability map, the first step of mapping performance is to create the expert model of the adjacency matrix to determine the correlation between all the performative indexes, as is shown in Table 7:

Table 7. The performative adjacency matrix

	Resource Access	Task Point Learning	Posting	Presentation	Online and Offline Interaction	Online and Offline Discussion	PBL Project
Resource Access	0	1	0	1	0	0	1
Task Point Learning	1	0	0	1	1	0	1
Posting	0	0	0	0	1	1	1
Presentation	1	1	0	0	1	1	1
Online and Offline Interaction	0	1	1	1	0	1	1
Online and Offline Discussion	0	0	1	1	1	0	1
PBL Project	1	1	1	1	1	1	0

- Mapping Performance Via Clique

Next, the performative matrix is input into NETDRAW to generate the idealized performance map, which is shown in Figure 3:

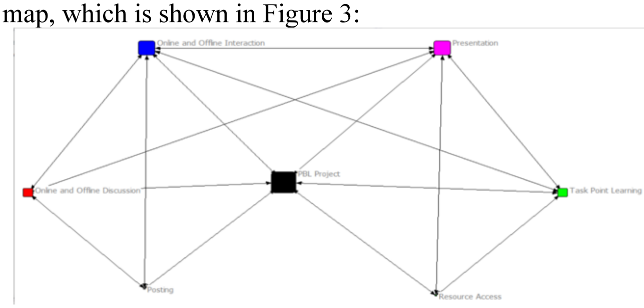

Figure 3. Teacher's performance map

In the performance map, the size of the squares representing the nodes in the graph indicates their degree and centrality. The following-up clique analysis in UCINET reveals the performative indexes may be divided into 4 cliques, as is shown in Figure 4:

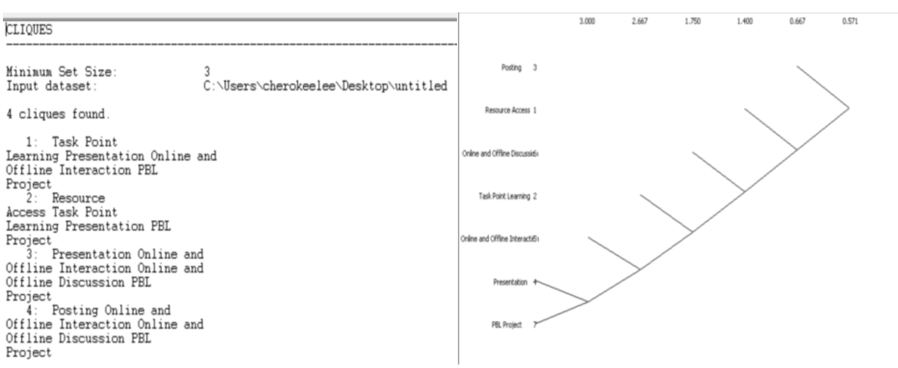

Figure 4. Results of clique and cluster analysis

It is quite obvious from the performance map and the results of clique analysis that the centrality and degree of the PBL project is the highest, for it appears in all the four cliques, suggesting it is the most important performative evaluation index, as is verified by the results of clustering analysis demonstrated in tree diagram which shows other performance path all lead down to PBL project. Performative indexes enjoying secondary centrality are online and offline interaction and presentation, which means the accomplishment of a PBL project requires plentiful online and offline interaction and presentation as a way of demonstrating learning outcomes glues the online and offline learning into the closed loop. Online and offline discussions and task point learning are at the tertiary level of centrality, then, at the lowest level of centrality are posting and resource access, suggesting they are all entry-level performative indexes.

Therefore, teachers should prioritize the score of PBL because learners' ratings in other performative evaluation dimensions such as online and offline interaction, online and offline discussion, presentation, task point learning, posting, and resource access are all rudimentary and preparatory, laying the foundation for their performance in the PBL project.

Afterwards, the performance evaluation indexes are paired with the indexes and a performative Q matrix is created to determine the correlation between them. To measure the actual attainment level of all performative indexes, each learner's actual scores of the performative evaluation items are converted into percentile decimals and input into the intersections in the performative matrix to replace the original binary value "1", which is shown in Table 8:

Table 8. A learner's performative Q matrix

	Resource Access	Task Point Learning	Posting	Presentation	Online and Offline Interaction	Online and Offline Discussion	PBL Project
Resource Access	0	1	0	1	0	0	1
Task Point Learning	1	0	0	1	1	0	1
Posting	2.66	0	0	0	2.66	2.66	2.66
Presentation	0.592	0.592	0	0	0.592	0.592	0.592
OnLine and Offline Interaction	0	1	1	1	0	1	1
Online and Offline Discussion	0	0	1	1	1	0	1
PBL Project	0.592	0.592	0	0	0.592	0.592	0.592

Finally, the performative Q matrix is input into NETDRAW for visualization; hence, that learner's performance map is generated, as is shown in Figure 5:

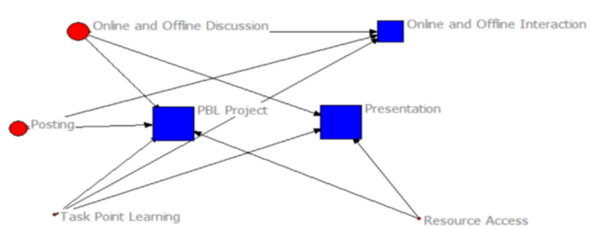

Figure 5. Learner's performance map

Through a comparative analysis of teacher's map in diagram 3 and learner's map in diagram 4, it can be inferred from the size of node figures that in learner's map, PBL project and presentation enjoy the same centrality, but the link between online and offline interaction and presentation is missing, so is the link between online and offline discussion, posting and task point learning. Moreover, task point learning enjoys less centrality as they do in the teacher's map, whereas posting enjoys more centrality. The author then reaches the diagnostic conclusion that learners may have spent too much time posting online, accomplishing PBL learning tasks and doing offline presentation, instead of carrying out self-adaptive independent learning and all the performative assessment tasks do not form the mutually supportive closed loop in learners' blended learning. Therefore, the proper performance intervention strategy may be individualized feedback, personalized and stratified resource recommendation.

Just like cognitive diagnosis, performance diagnosis may also be enacted via density, in which each learner's performative Q matrix with actual score values is input into UCINET to measure the degree which reflects the closeness or connection strength between the performative evaluation items and indexes, and the results will be divided by the degree of teacher's performative map to get learner's performative attainment ratio, which is shown in Table 9:

Table 9. Learners' performative attainment ratio

Student Number	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Density	0.62	0.78	0.66	0.68	0.4	0.728	0.71	0.46	0.53	0.75	0.57	0.55	0.46	0.49	0.54	0.48	0.49	0.45	0.55	0.76
Attainment Ratio	0.87	1.1	0.92	0.95	0.56	1.02	0.99	0.64	0.75	1.04	0.79	0.77	0.64	0.68	0.76	0.68	0.69	0.63	0.77	1.07

Compared with the density of the expert performative map 0.7143, the performative attainment ratio suggests only 4 out of a sample size of 20 attained the expected performance level.

The last procedure to close the cognitive and performative mapping in this research is to make the correlation analysis of the cognitive and performance attainment ratios and cognitive and performative density in SPSS 26.0. In a bivariate correlation analysis taking cognitive attainment ration and performative attainment ratio as variables, the Pearson correlation coefficient is 0.394, and the same result is obtained in the bivariate correlation analysis taking cognitive density and performative density as variables, which means the two sets of variables are positively correlated.

5. Discussion

The desirable outcome of cognitive and performative mapping is the whole network of learners' language-specific cognitive abilities and learning-specific performance which represents learner's learning network, social interaction and language ability development.

Technically, digital evaluation in higher foreign language education requires the incorporation of digitalized formative data into the network analysis of language skills, in which structured performative data such as timestamp, system logs, platform records, classroom observation records generated in online and offline learning events are related to many unstructured natural language data generated in language tests and digital evaluation tasks, such as learners' articles, conversations, essays, projects, or creative works.

The digital evaluation of a learner's performance requires the evaluation of the student's online and offline interaction, cooperation, and information sharing, which helps teachers analyze the structure and working of the learner's social network to enhance the quality of social support.

In the digital teaching environment, learners' engagement in PBL projects are manifested in their contribution, cooperation frequency, and communication modes, which can all be encapsulated in the whole network analysis. The results of whole-network-based collaborative project evaluation provide very effective dynamic feedback to learners. Furthermore, learners' self-directed learning behavior, such as self-propelled information retrieval and learning plan development, can all be measured through a performative whole network.

6. Conclusion

This research introduced a mapping framework for analyzing the data collected from blended teaching practice. With the SNA analytic paradigm, a teacher can evaluate learners' socio-cognitive development and performance, using software tools and formative evaluation index system. The whole-network-based mapping of cognition and performance projects a new developmental perspective for the digital evaluation in higher foreign language education and produces a holistic and dynamic interpretation of learners' current language proficiency, learning aptitude, and learning experience via classroom observation, stressing the spiral escalation of language testing, feedback, training and interaction.

The principal contribution of the research is the introduction of density and attainment ratio in SNA as effective predictors in digital evaluation. The weighted density and clique analysis can help teacher identify learning deficiencies and provide timely intervention. In this research, density is used to evaluate the inherent interconnection between all the cognitive and performative indexes. Moreover, this research puts forward a new computational model of attainment ratio for digital evaluation, mediating a better understanding of how individualized learning experience can be digitally structured and graphically presented for predictive diagnostics and precise intervention.

The research also contributes a graphical method to the digital evaluation of learner's learning trajectories, supplementing previous research with experimental visualization approaches.

To summarize, the whole-network-based mapping model postulated in this research satisfies three basic prerequisites of digital evaluation:

(1) Personalization. The cognitive and performative whole network generated in mapping procedures are necessary steps towards a holistic digital evaluation. With the input of learners' actual scores, the expert model of cognitive and performative whole network turns into the unique cognitive ability map and performance map for each learner, in which all the evaluation items and indexes are interdependent in understanding learners' learning style, aptitude and need.

(2) Traceability. All the cognitive and performative data used in the generalization of cognitive and performative whole network can be traced back to specific blended teaching and learning processes and events.

(3) Visualization. After building the adjacency or Q matrices for the whole network analysis, the correlation between cognitive and performative data sets and evaluation items is graphically mapped via digital tools and software like UCINET and NETDRAW.

In terms of limitations, on the one hand, given the limited size of the dataset, the validity of the mapping paradigm postulated in this research still needs large-scale empirical proof. On the other hand, the mapping of cognition is far more intricate and complicated than the author has imagined and the relationship between cognitive elements and tested items needs to be verified by constructing a knowledge map, which is an area for future exploration.

To conclude, the alignment between a whole network analysis and digital evaluation could be consummated by constructing a knowledge map of foreign language learning and teaching. Although the mapping method for digital evaluation is still in its early stages, the author hopes that the taxonomy of cognitive and performative data could be further applied to multi-modal data mining and learning analytics.

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