AC 2012-4747: DECIPHERING STUDENT IDEAS ON THERMODYNAMICS USING COMPUTERIZED LEXICAL ANALYSIS OF STUDENT WRITING

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Deciphering student ideas on thermodynamics using computerized lexical analysis of student writing

Abstract

Constructed responses, in which students describe their understanding in their own language, provide better insight into their thinking than do multiple-choice assessments. However, constructed responses are not often employed in large enrollment courses due to the time and resource constraints involved in grading these assessments. In this study, we examined student understanding of thermodynamics using computerized lexical analysis of constructed responses in a large enrollment course (N=294). Students were asked to interpret a graph depicting changes in free energy during the course of a reaction using both multiple-choice and constructed responses. Constructed responses were analyzed using SPSS Text Analytics for Surveys (TAFS). The software extracts scientific terms from the students' writing and places them into categories using custom dictionaries of science terms. We validated the automated lexical analysis by using the categories created by TAFS as independent variables in discriminant analysis to predict expert scoring of the students' writing. Our findings reveal i) that students hold a heterogeneous mix of correct and incorrect ideas about thermodynamics, and ii) that this heterogeneity is undetected by multiple-choice testing. Almost 50% of the students answering multiple-choice correctly displayed incorrect, or both correct and incorrect conceptualizations in their written responses. Our results support previous studies that have revealed students' heterogeneous ideas about matter and energy conservation and acid-base chemistry using lexical analysis. These findings suggest that computerized lexical analysis can improve instructors' understanding of the heterogeneity of ideas that student harbor about key concepts in STEM disciplines and inform assessment practices

Introduction

Over the past twenty years, there has been increasing focus on the development of initiatives to improve STEM education [1–3].The use of formative assessment can help instructors gain better understanding of student learning in STEM disciplines [4–6]. Authentic and effective assessment provides students with the opportunity to demonstrate their understanding and allows instructors to give feedback on students learning. However, the prevalence of large-enrollment STEM courses, particularly at the introductory level, has led to the use of multiple-choice assessments, which are cheaper and less time-consuming to implement and grade.

Multiple-choice assessments may not elicit student conceptualization of the subject material [7].The format encourages students to select from a list of options and may encourage the use of elimination to arrive at their final choice [8]. Yet research has shown that instructors need a clear perception of students' current knowledge to confront misconceptions or incorrect ideas and foster the creation of scientific constructions [9,10]. Constructed responses, sometimes referred to as open-ended or free-response, allow students to demonstrate their own understanding of the subject matter, and are more effective for diagnosing student misconceptions compared to multiple-choice testing [11]. However, one obstacle to the use of constructed-response assessments has been the time investment and expense involved in grading these assessments.

The Automated Analysis of Constructed Responses (AACR) research group at Michigan State University explores student understanding expressed in constructed responses using computerized lexical and statistical analyses. Lexical analysis of constructed responses can minimize the time and costs involved in scoring constructed responses assessments, and facilitate timely teaching interventions. This approach allows students ideas to be extracted from their responses and categorized automatically giving instructors an insight into student thinking, thus making formative assessment and feedback feasible even in large-enrollment courses.

A fundamental understanding of thermodynamics is necessary in many STEM discipline including physics, engineering, chemistry and biology, and it is frequently taught in many large-enrollment introductory courses. Students often harbor misconceptions about or have problems understanding thermodynamics [12,13], including the relationship between exothermic, endothermic and spontaneous process and distinguishing between the system and surrounding, which can be uncovered using written assessments [14]. In this study, we demonstrate the use of automated text analytics software to investigate students' understanding of thermodynamics in an introductory biology course. We examine the relationship between students' multiple-choice and constructed responses to a thermodynamics question pre and post instruction. We further investigate the heterogeneity of and connections among ideas presented by students written responses using text analytics.

Study Methods

Study Question

Our study was conducted in an introductory cell and molecular biology course during the fall semester 2008 at a large state university. At least one semester of chemistry is required as a prerequisite for this course and students were expected to have a basic understanding of thermodynamics. Students were given online homework assignments including a question on free energy consisting of a multiple-choice and constructed response component (Figure 1).

Question (correct answer in bold).
Study the graph that illustrates the chemical reaction A +B $\rightarrow$ C + D. Does this graph represent an exergonic or endergonic reaction?

A. Endergonic
B. Exergonic
C. Either

How can you tell?

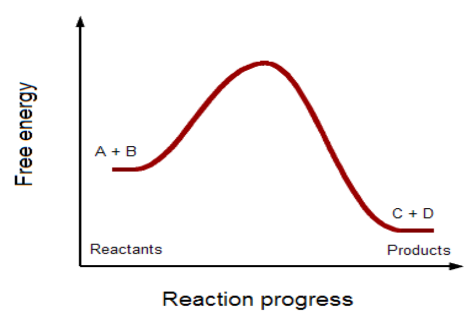


Figure 1. Questions and supporting diagram given in pre- and post-instruction online assignment.

The assignment was administered pre- and post- instruction. Students were given credit for completion of the assignment regardless of the accuracy of their answer. 294 responses (168 pre-instruction and 125 post-instruction) were collected using the online learning management system. Post-instruction responses were independently scored by two raters with expertise in biology and chemistry. Correct and complete responses described the components of the system and the change in free energy (see examples in Results section below). The raters scored responses that had only correct ideas as 1. Responses with incorrect, incomplete or mixed (both right and wrong) ideas were scored 0. Demographic data was also collected to characterize the student population.

Text Analysis

We used IBM SPSS Text Analytics for Surveys 4.0 software[15] to analyze constructed responses. The software identifies *terms* from custom-built libraries [16,17], similar to dictionaries. (For more details on the operation of the software see references 15 and 16). Terms are classified into *categories* by predefined computer algorithms which are subsequently modified by the researcher. Each response can contain multiple terms, with each term belonging to one or more categories. The software also displays *web diagrams*, similar to those in Figure 4, illustrating the connections among categories within groups of responses. Appendix I summarizes the approaches used in this study in the form of a flow chart.

Statistical analysis

We used IBM SPSS Statistics 19[18]to conduct independent t-tests to compare the distribution of categories pre- and post- instruction and categories for correct and incorrect/incomplete responses, with Bonferroni corrections for multiple comparisons ($p<0.003$). We conducted discriminant analyses to determine categories that predict correct and incorrect post-instruction responses. The discriminant analysis used a stepwise-forward, Wilk's method with an F-in of 3.84 and F-out of 2.71. We used group sizes for prior classification probabilities and a leave-one-out cross validation.

Discriminant analysis is similar to linear regression and determines a linear function that expresses the relationship between dependent and independent variables. However, in the case of discriminant analysis, the dependent variables are categorical instead of interval. For this analysis, we have a series of binary independent variables (presence or absence of a student’s response in a lexical category) which are combined to predict categorical dependent variables (expert rating). In this analysis the dependent variables has two categories (correct and incorrect) which results in a single linear function. Discriminant analysis analyzes the covariance between independent variables, or whether the variables change together or not. Because of this, it is not the values of independent variables but the relationship among them that is critical in determining the discriminant functions.

Results

Our student population was 60% female with an average GPA of 2.98 on a 4.0 scale. The class was composed of 59% sophomores, 26%juniors, 9% seniors and 6% freshmen from mostly STEM disciplines (Table 1.)

Table 1. Distribution of majors of study student population

Major	Percent of Respondents (%)
Pre Med/Dental/Nursing/Vet	30
Human Biology	17
Natural and Animal Science	10
Social Science	8
Nutrition	7
Zoology	7
Biochem/Microbiology/Genetics	3
Kinesiology	2
Engineering	2
Physics	1
Chemistry	1
Other	5
Undeclared majors	7

In the pre-instruction assignment 76.8% of the student chose the correct multiple-choice answer. Post-instruction this percentage increased to 84.9%. However, 49% of students selecting the correct multiple-choice response had incorrect explanations for the type of reaction in the post test. Raters demonstrated high scoring agreement (Cronbach's alpha = 0.88) and scoring disagreements were resolved by consensus. Correct and complete responses compared the free energy of the reactants and products or referred to the net negative change in free energy for the reaction. The following are examples of correct responses:

> Correct response 1: "energy is released as the reaction proceeds, with the products having less energy than the reactants"

> Correct response 2 "The change in G is negative which implies the reaction is giving off energy"

Incorrect responses were either incomplete, completely wrong, or contained both wrong and correct ideas. The following are examples of responses scored as incorrect:

> Incorrect Response 1 - Incomplete response: "releases energy" (This was the entire explanation submitted.)

> Incorrect Response 2 - Only wrong ideas: "The energy is transferred from the reactants to the products"

> Incorrect Response 3: Both correct and incorrect ideas, "You can tell because the reactants have more potential energy than the products. Also because there is a loss of free energy this reaction gives off heat."

We used lexical analysis to uncover the ideas in students' explanations. Text analysis successfully categorized all 294 responses into one or more categories. Categories (*in italics*) were first automatically generated by software and refined by researchers. For example, the category *products,* which automatically extracted words and phrases containing the word product, was modified by researchers to include references made to" C+D". This was important to capture, for in lieu of the word "products" several students mentioned C+D, the symbols representing products in the question diagram. The categories described included

i. components of the reaction (*reactants* and *products*),
ii. energy (*free energy* and *energy*),
iii. reaction types (*exergonic*, *endergonic*) and
iv. energy changes (*lower*, *release*, *higher*).

The frequency of pre-and post- instruction responses were similar among the 14 categories ($p>0.05$; t-tests) (Figure 2). All categories represented in at least 5% of the responses are shown. However, post-instruction, we see a difference in the distribution of categories in correct and incorrect response (Figure 3). Post-instruction more responses included the categories *reactants, products*, *free energy* and *lower*. Correct responses also contained terms like *delta G, exothermic, endergonic*, which were absent from incorrect responses. These were further examined using discriminant analysis.

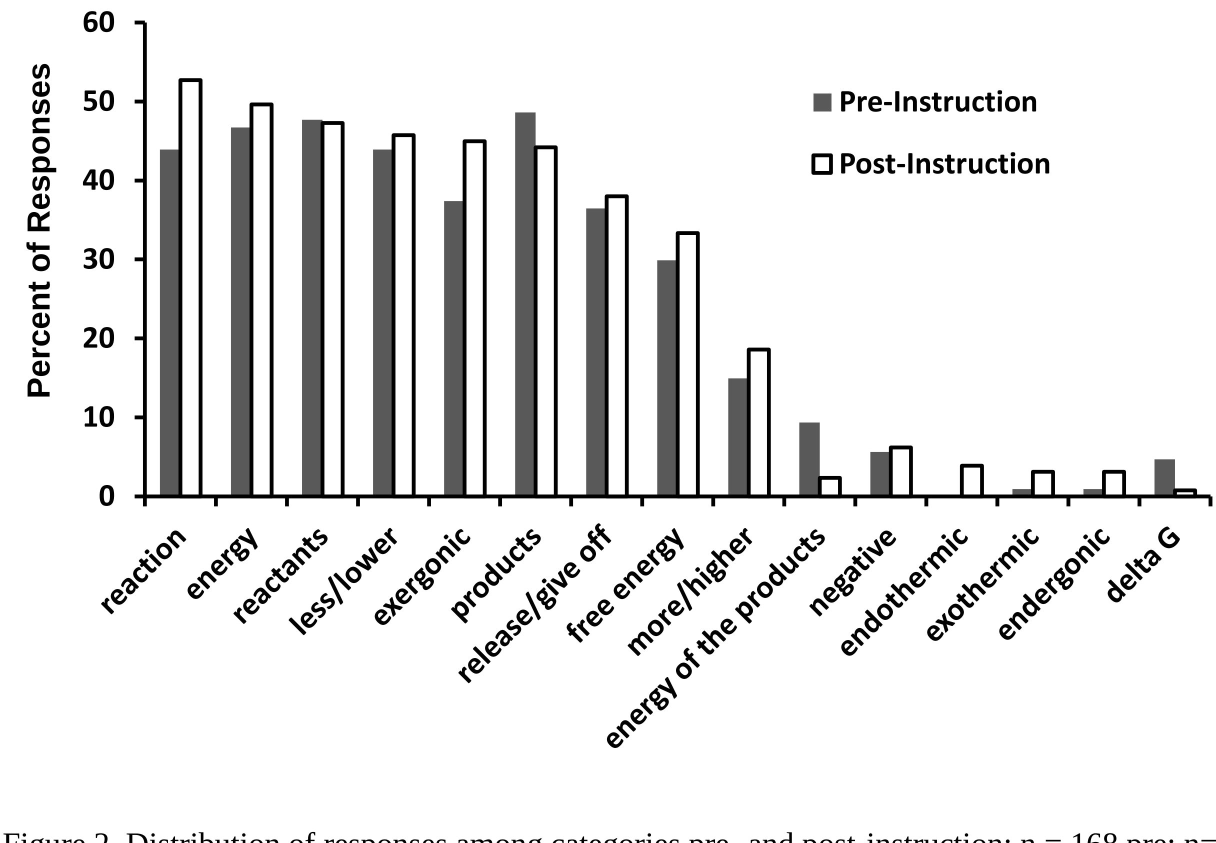


Figure 2. Distribution of responses among categories pre- and post-instruction; n = 168 pre; n= 125 post

We used discriminant analysis to validate the categories from lexical analysis as the independent variables and expert scores (correct or incorrect) as the dependent variables. The use of stepwise model allows only categories that are significant to the model to be included. We used a leave-one-out classification for cross-validation. The resulting discriminant function was significant (Wilks Lambda = .629, Chi-square 47.111, df = 5, p <0.000). Discriminant analysis of post-instruction responses identified 5 categories that significantly predicted correct and incorrect responses (Table 2). These categories were used to construct web diagrams illustrating the frequency of responses and connections among the categories (Figure 4).

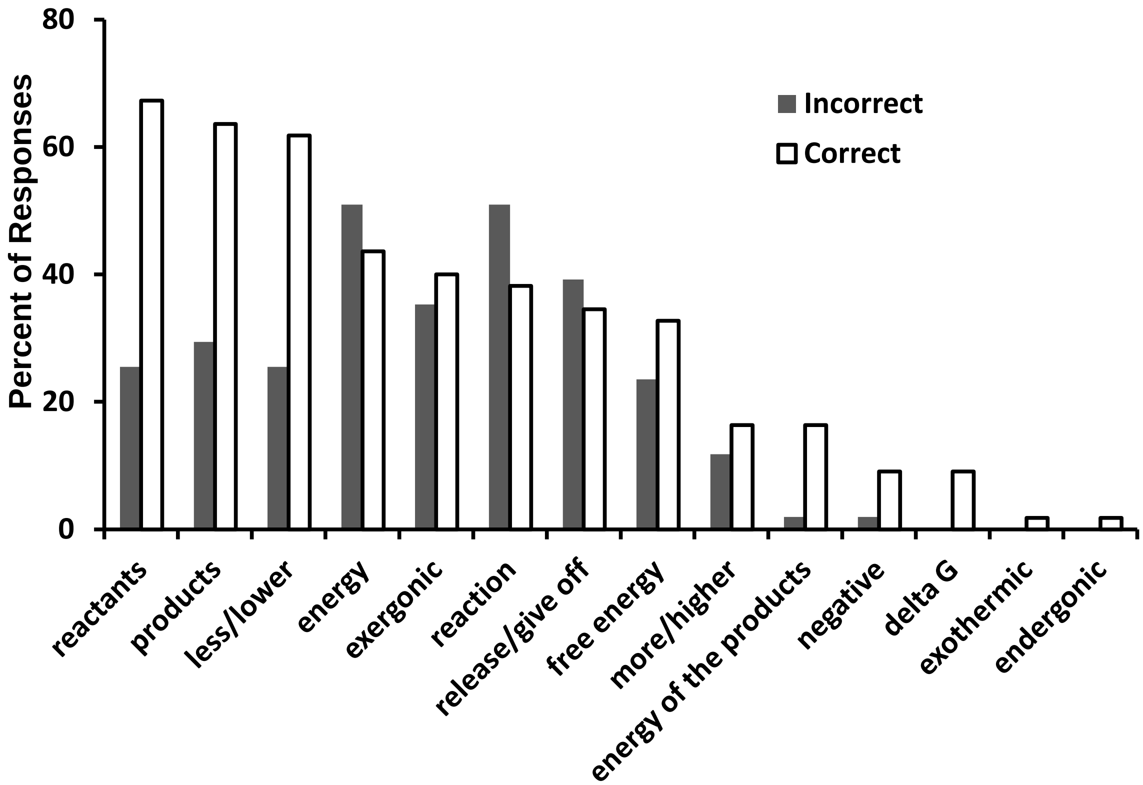


Figure 3. Distribution of correct and incorrect responses among categories; n=125

Table 2. Standardized canonical discriminant function coefficients.

Category	**Coefficient**
Delta G	0.525
Energy of the products	0.502
Products	0.492
Lower	0.469
Reactants	0.360
Computer- Human Scoring Inter-rater reliability	Cronbach’s Alpha = 0.75

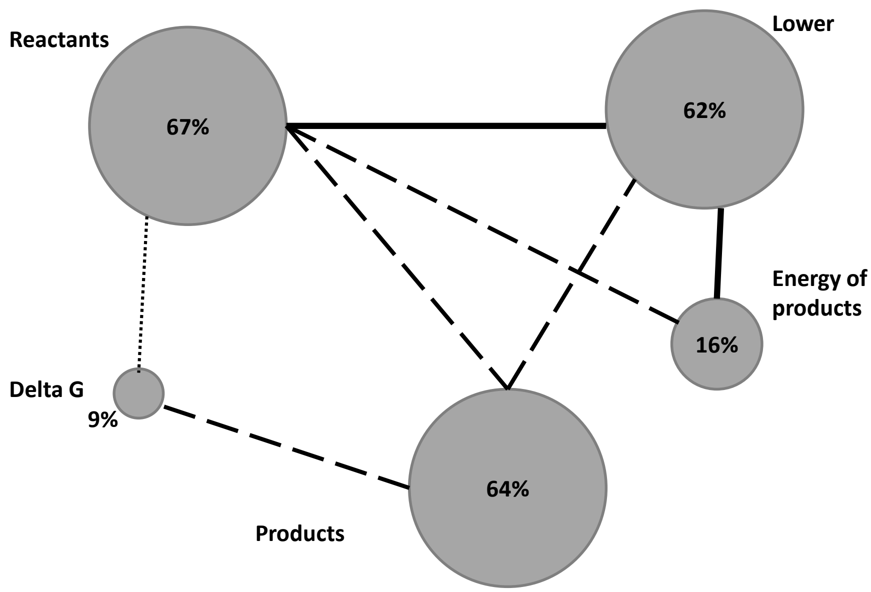
Web diagrams illustrated distinct differences between correct and incorrect responses (Figure 4 a and b, respectively). Correct responses had considerably larger node sizes indicating the more correct responses contained these predictive ideas (i.e. *reactants*, *products*, *energy of products*, *lower* (energy). Correct responses also contained terms in the category *delta G* while incorrect responses did not.

We also observed more co-occurrences among categories in the correct responses than among categories in the incorrect responses web diagram. These co-occurrences are also more frequent as represented by the solid line between the nodes *reactants* and *lower* in the correct response web diagram. These connections reflect the comparisons made by students giving correct responses, such as the response "…with the *products* having *less* energy than the *reactants*" which contained 3 ideas. In contrast, the fewer or weaker connections among incorrect responses were indicative of several incomplete responses such as "the *products* have *less* free energy", in which students expressed fewer ideas.

Discussion

Lexical analysis of student responses to the thermodynamics question demonstrated patterns in student thinking and can indicate whether students have appropriate conceptualizations of the material. Although most students in our study could select the correct multiple-choice option post-instruction, only half of these provided complete and correct explanations for their choice. Problems understanding endothermic and exothermic process can be prevalent among students learning thermodynamics[12,14]. Additionally, the large number of students who were unable to describe the change in free energy in the system may harbor difficulty indistinguishing between the system and surroundings , another common misconception held my students[12]. Our results demonstrate that this gap in student understanding could be undetected with only multiple-choice testing, but was revealed through written assessment, as has been observed in other fields [7,8].Our findings support previous studies in which lexical analysis of constructed responses revealed heterogeneous conceptualization in photosynthesis [19,20] and acid-base chemistry [17]

a) Correct Responses



b) Incorrect Responses

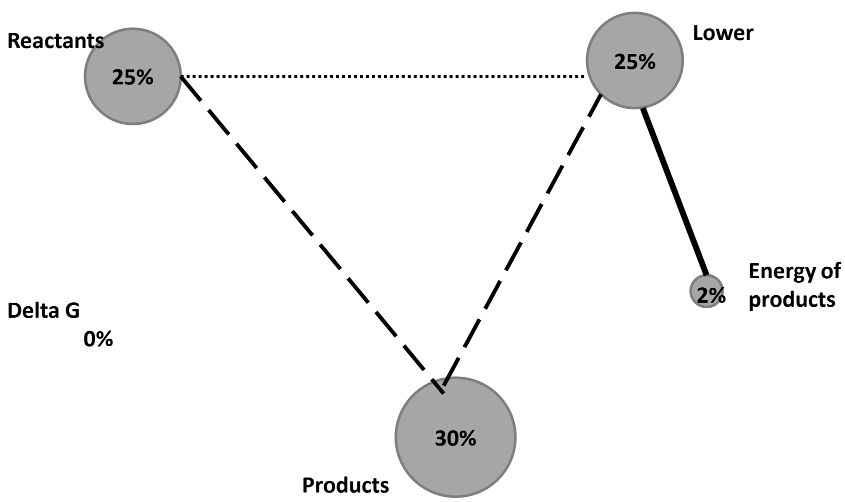


Figure 4. Web diagram of categories and links for a) Correct and b) Incorrect responses. Each category is represented by a node. The size of the node corresponds to the frequency of responses containing a category. Lines indicate the percentage of shared responses. Solid lines ——— indicate that 75% shared responses; dashed lines — — — 50-74%, dotted lines ....25-49%. Nodes with fewer than 25%share responses were not linked.

One limitation of this lexical analysis is that it does not take into consideration the proximity of terms. Examination of responses that were misclassified by the discriminant analysis suggests that some responses could be better scored if the proximity of terms, along with the frequency of terms, could be determined. This would give additional granularity to categorization, if the text analytics program could determine whether students used the terms “products" within 2 or 3 words of ”less/lower” and “energy”, but used term “reactants” further on in their discussion. However even without this granularity, we observe that the connections among terms are stronger for correct responses that are characteristic of students who used comparative statements. Students with incomplete ideas did not express a full comparison of the free energy states of both products and reactants as demonstrated by the weaker or dashed lines in Figure 4. Similar patterns were observed for students understanding of the acid/base chemistry [17] . The exploration of programs which examine proximal relationships among word is an avenue for our future research in lexical analysis of written responses.

Future Directions

This study is one of a growing body of research which demonstrates the utility of constructed assessments coupled with automated analysis to understand student learning [17,19–22]. At this stage of development, lexical analysis of written responses requires substantial investment of time and resources to develop items, conduct the lexical analysis, score student responses and develop statistical models [22]. We are continuing to develop these resources through collaborations with other disciplinary based education researchers in the STEM fields [23]. As these resources become more widely available, instructors will be able to select from a large number of questions, administer the question(s) in an online assignment, run the student data through text analysis software, and compare results with previously developed models. The resource and time investment spent on analysis becomes minimal for the instructor, allowing him/her to invest the greater proportion of his/her time in reviewing the analysis to identify areas where students show misunderstandings and designing interventions to address this in the next class.

Constructed response assessments evaluated using lexical analysis tools provide insight to both individual and class-level thinking. Individual students’ ideas can be parsed into correct or incorrect categories based on discriminant analysis models. At the class-level, lexical analysis allows visualization of the connections among ideas for the student population as a whole. Web diagrams revealed that students with a weaker understanding of the free energy showed fewer links between ideas. We do not suggest that the results of this lexical analysis and the discriminant function be used to assign grades to individual students. However, this assessment and evaluation approach would allow instructors to design instructional interventions that challenge misconceptions and clarify areas of confusion before the final summative assessment is given.

Future research will include item construction and analysis of other written assessments on reaction thermodynamics to examine patterns of student understanding elicited by questions designed to examine comprehension and application of the subject matter. We will also examine how students understand the thermodynamics spontaneous reactions and the application of thermodynamics to biological reactions.

This study demonstrates that written assessments coupled with computerized lexical analysis can be used to uncover students' thinking about scientific concepts in large-enrollment courses. The combined use of lexical and statistical analysis provides a map of the complexity of ideas that students hold. In the future, this approach can provide a mechanism for instructors to obtain rapid feedback on their teaching and student learning which can drive the next phase of instruction, especially in large-enrollment courses.

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Appendix I: Methods Flow chart