Moving towards problems assignments with reduced goal-specificity in introductory STEM courses

Vazgen Shekoyan and Wenli Guo

***Abstract*—Are solving standard end-of-chapter problems found in typical STEM textbooks an effective way of helping students to become better problem solvers? For instance, does it encourage students to choose more expert-like strategies during the solution process? Does it help students gain better conceptual understanding of the content material? Research shows that the answer to the above questions is negative. Studies on expert-novice differences and on cognitive processing suggest that the potential reason is the goal-specificity of traditional problems. Solving problems without a specifically defined goals (reduced goal-specificity problems) leads to higher learning outcomes than solving problems with a specifically well-defined goal, usually specified as a specific goal state that has to be reached (e.g., finding numerical value of a specified variable). We have designed and incorporated a set of reduced goal-specificity physics problems in an algebra-based physics course for engineering technology students at Queensborough Community College. Such problems ask students to find numerical values of as many variables as they can rather requiring determination of numerical values of specific goal variables. The implications of the implementation have been evaluated in a quasi-experimental control-group design study. It is the first time that such problems are created and embedded as an integral part of a college level science course (an ecological setting). We discuss here the implications of the implementation as well present examples of how to turn goal-specific end-of-chapter problems into reduced goal-specificity problems.**

***Index Terms*— Alternative problems, cognitive load, engineering students, goal-specificity, ill-structured problems, physics education, problem-solving, schema acquisition.**

I. Introduction

Studies of workplace needs indicate that problem solving is one of the most important skills STEM students need to acquire [1]-[6]. The ability to identify, formulate and solve engineering problems is listed as one the essential ABET criteria [3]. Do traditional problems resemble at all the types of problems students encounter in the workplace? Are traditional problems effective in helping students build problem solving expertise?

Firstly, most of real life and professional problems are ill-structured (multiple-possibility problems). Such problems a) often have missing information, *vaguely defined goals* or unstated constrains, b) possess multiple solutions with multiple criteria for evaluating the solutions, and c) present uncertainty about which concepts, rules, and principles are necessary for the solution [7]-[8]. In educational settings we polish problems and make them well-structured (single-possibility problems). One of these "polishing" steps is making the problem goals well-specified (as opposed to leaving them vaguely defined).

Secondly, when students are facing end-of-chapter regular problems they rarely use expert-like strategies (e.g., forward-chaining method) to tackle them. In fact, most of the time their novice-like strategies (e.g., backward-chaining method) are sufficient for finding answers to the problems. However backward-chaining method leads to low scheme acquisition or rule induction and imposes higher cognitive load on the solver [9]-[10]. An extensive discussion of this topic is presented in Section II.

Research also shows that traditional problem solving is not effective in helping students learn science concepts. For instance, Kim and Pak [11] found that there is little correlation between the number of regular, well-structured problems the students solved and their conceptual understanding. They assessed students who solved large number of end-of-chapter physics problems (the range was from 300 to 1500 problems). The students did not have much difficulty in using physics formulas or mathematics. However, they still retained common difficulties in the understanding of basic concepts of physics. Hence, the commonly suggested cure of "assigning more problems to help them learn physics" did not work. It is likely that inclusion of alternative type of problems such as multiple-possibility problems could help improve students' conceptual understanding of scientific concepts [8]. Reduced goal-specificity problems are a sub-category of multiple-possibility problems.

In Section II we provide literature review on the effects of problem goal reduction on learning and problem solving skills. Section III provides the description of the design of reduced goal-specificity physics problems (will use an abbreviated

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name for such problems: reduced-specificity problems). Few of such problems are provided as well. We have incorporated those problems in an algebra-based physics course for engineering technology students at Queensborough Community College (QCC). Its implication on student problem solving is evaluated in a quasi-experimental control-group design study. The results of the study are presented in Section IV.

II. LITERATURE REVIEW

A series of studies have been conducted [9], [11], [12] to analyze the role of goal-specificity reduction of problems on solvers. For problems with reduced goal specificity researchers used standard kinematics, geometry and algebra problems with modified tasks. Instead of asking students to calculate a numerical value of a specific variable in a problem they asked students "to calculate the value of as many variables as they can." Such modifications are possible only for special types of problems that are classified by Greeno [13] as transformation problems.

Transformation problems consist of an initial state, a goal state and legal problem-solving operators. For example, a problem that asks to find the acceleration of an object with a given mass and known interaction forces is a transformation problem where the initial state is given by the known variables of the problem (e. g., mass, magnitudes of interacting forces, initial positions of the objects), the goal state is the value of acceleration and the problem-solving operators are Newton's Second Law equations. The majority of problems assigned to students in traditional introductory physics courses are transformation problems [9], [14].

In order to discuss the role of reduced goal-specificity on problem-solving one needs to know what students learn when solving traditional goal-specific problems, and what problems-solving methods (or general methods) they use and how it affects their performance.

Working-forward and working-backward methods

Research shows that experts tend to use strong, domain specific methods or strategies while solving problems in their domains of expertise, such as working-forward analysis. Novices tend to use weaker methods, such as working-backward analysis (i.e., means-ends analysis) [15]-[18]. Working-forward analysis and working-backward analysis methods are often called forward-chaining and backward-chaining strategies or methods as well.

In a working-forward method the problem solver starts at the beginning (from the givens) and tries to solve the problem from the start to the finish. In a working backward method the problem solver starts at the end (from the goal) and tries to work backward from there. In particular, in a working-backward method the problem solver analyzes the problem by the viewing the end (the goal being sought) and then tries to decrease the distance between the current position in the problem space and the end goal (or goal position) in that space. The fundamental axiom of means-ends analysis is the following:

At each problem state the solver selects operators that will reduce the differences between the problem state and the goal state [15].

According to Newell's conjecture [15], working-backward method is considered more general, less domain specific whereas working-forward method is typically more domain specific method. Thus, the solver would have to use much less domain specific knowledge while attempting to solve well-specified problem. This casts a doubt on a general conviction (such as expressed in [19]) that assigning end-of-chapter standard transformation problems to students strongly reinforces their mastery of the domain knowledge.

Expert-novice studies; problem solving schemata

Expert-novice studies have shown that the primary factor distinguishing experts from novices in problem solving abilities is the domain specific knowledge in the form of schema (e.g., [20], [16] and [17]). Schema (plural form: schemata) is "a cognitive structure which allows problem solvers to recognize a problem state as belonging to a particular category of problem states that normally require particular moves. This means, in effect, that the problem solver knows that certain problem states can be grouped, at least in part, by their similarity and the similarity of the moves that can be made from those states". Novices who lack experience in problem solving in the domain do not posses appropriate schemata, so they are left with the option of using more general problem-solving methods such as means-ends analysis.

Some of the key observations leading to this conclusion are based on the work of Larkin and colleagues [18], [20]. Larkin contrasted the way in which students and professional physicists tackled non-trivial problems in mechanics. The students' problem solving steps were close to means-ends analysis; they contrasted what they know with what they needed to know to solve the problem, and then asked what operations could develop the necessary knowledge. They searched for an equation that contains the goal variable as an unknown and tried to solve it. If the equation contained another variable with an unknown value, they tried to find another equation to solve for that unknown, and proceed in this manner until the answer is found.

Experts behaved in a quite different way. They classified the problem as being a specific example of a particular class of physics problems (e. g., balance-of-force problems). Then they used these classifications to retrieve from memory an appropriate schema for solving the general class of problems. Once the schema is retrieved, they solved the problem in a forward-working manner, by writing the general equations and then solving for the appropriate unknowns until the goal variable is calculated. The results have been corroborated by the famous Chi study [21], where both experts and novices were asked to categorize mechanics problems based upon similarity of solutions. As opposed to experts, novices categorized problems based on superficial aspects of problems (such as inclined plane problems, pulley problems, block problems, etc).

Selective attention, Cognitive processing load and Schema acquisition

Since experts use schemata to solve problems in their domain of expertise, one of the desirable learning outcomes of student problem solving would be schema acquisition.

What factors should one expect to hinder schema acquisition when the solver is using means-ends analysis to solve a problem? There are two important related factors one has to consider: selective attention and limited cognitive processing capacity [9].

When students are solving a problem by means-ends analysis method, they must pay attention to differences between a current problem state and the goal state. Previously used problem-solving operators and the relations between problem states and operators can be ignored by problem solvers using this method under most conditions. Previous steps and operators may be noted only to prevent retracing steps during solution.

However, for acquiring a schema, a problem solver must learn to recognize a problem state as belonging to a particular category of problem states that require particular moves. So, paying close attention to the problem states previously used and the moves (operators) associated with those states should be an important component of schema acquisition. Because schema does not depend on the problem goal, it would lead to the usage of forward-working methods.

The cognitive load imposed on a problem solver using means-ends analysis is the other factor. According to Sweller [9], in order to use a means-ends analysis method, a problem solver must simultaneously consider the current problem state, the goal state, the relation between the current problem state and the goal state, the relations between problem-solving operators, and the order of sub-goals used (if any were used). The amount of cognitive-processing needed to handle this much information may be a cause of cognitive overload, and even if the problems is solved, it would leave little for schema acquisition. After all, one need to keep mind that our working memory is limited, and typically one cannot hold more than 7 chunks of information at a time [22].

To summarize, according to Sweller [9], the major reason for the ineffectiveness of conventional problem solving as a learning device, is that the cognitive processes required by the means-ends analysis and schema acquisition activities overlap insufficiently, and that conventional problem solving in the form of means-ends analysis requires a relatively large amount of cognitive processing capacity which overloads working memory. The hypothesis of human problem solvers' cognitive overload of working memory during means-ends analysis is the backbone of his widely-known Cognitive Load Theory [10].

Sweller hypothesizes that reduction of goal specificity in problems not only causes a decrease in the novice solvers' cognitive processing load, but also makes them to rely more on expert-mode forward-chaining methods, and by doing that enhance schema acquisition. In addition, he claims that it will cause enhancement of transfer as well, which means that novices become more successful in solving similar problems in the domain.

Empirical evidence

In this subsection we will briefly present the empirical bases to the claims in the above-mentioned paragraph (keeping the main focus on the physics problems they used).

The main reduced-specificity problems used in Sweller's and colleagues' papers were 1) Tower of Hanoi puzzle [11]; 2) maze-tracing puzzles [11]; 3) few geometry [12, 9] and algebra problems [11]; and 4) few kinematics problems [12].

We describe here only the kinematics problems. They used two categories of constant-acceleration kinematics problems: in one, the final speed was the unknown; in the other, the unknown was the distance traveled. In all these problems the objects start moving from rest. So the initial speed is always zero. The participants were constrained into using only three equations.

Here are examples of such problems from each category ([12], p. 643):

In 18 sec racing car can start moving from rest and travel 305.1 m. What speed will it reach?

A pile driver takes 3.732 sec to fall onto a pile. It hits the pile at 30.46 m/sec. How high was the pile driver raised?

The specificity of the problem would be reduced if the solver is asked “to calculate the value of as many variables, as she or he can”, instead of just calculating the value of one specific variable, e. g, the final speed.

14 mathematics graduates taking teacher education courses were assigned goal-specific kinematics problems similar to the ones shown above. The students were solving those problems through a computer-controlled visual display screen (usage of pencil and paper was not allowed.) Students were allowed to proceed to the next problem only after they had solved the preceding problem correctly. After solving 77 problems (25 different problems were used, but thirteen of them were used five times in different order) students demonstrated the switch from means-ends to a working-forward method. Also they demonstrated a decrease in the number of moves required for solution of some problems. So, only after getting an extensive experience (in this case, solving 77 problems) students could switch to expert-mode problem solving. This means that in the context of such kinematics problems students can develop problem-solving expertise by solving many goal-specific problems. What would happen if we give students fewer problems but instead make some problems reduced-specificity problems?

In another set of experiments (the computer-based setup used was identical to previous experiment's setup) two different groups of students (20 high-school students) were used. One group worked a set of 20 goal-specific kinematics problems. The other group also worked on 20 problems; however 10 problems were reduced-specificity problems. In these problems students were asked "to calculate the value of as many variables as they can." At the end of the session significantly more of the students in the latter group developed forward-working strategies. Similar experiments were conducted with geometry problems with same results.

So, these experiments supported the hypothesis that the use of non-specific rather than specific goals enhanced the use of forward-working strategies as well as the rate of schema acquisition.

Additional evidence of positive impact of reduced goal-specificity on problem solving and transfer was found by Vollmeyer and her colleagues [24]. They performed experiments within a complex dynamical system (they used a complex biology problems with specific and non-specific goals). Performance of those participants who were initially tackling the non-specific goal problem was significantly better on the subsequent transfer problem than performance of those participants who instead were tackling the goal-specific problem. The transfer problem was similar to the initial problems but with a new goal.

The hypothesis that the main reason of the ineffectiveness of means-ends analysis is cognitive overload was tested by Sweller in [9]. One way Sweller tested the hypothesis was through developing a computational model of solving transformation problems in kinematics via forward-working and means-ends analysis methods. The model was constructed using PRISM, a productive system language designed to model cognitive processes [25]. Cognitive load was measured by counting the number of statements in the program's working memory, the number of productions, the number of cycles to solution and the total of conditions met. The model showed that the cognitive load was much bigger for means-ends analysis solution.

Another way Sweller tested the hypothesis was through assigning participants geometry problems with and without specific goal and then measuring participants' performance errors such as numerical errors or misuse of equations [9, 26]. Four to six times as many mathematical errors were made by goal-specific groups compared to nonspecific goal groups. This shows that by attempting to solve problems via means-ends analysis the goal-specific groups suffered from cognitive overload that manifested itself by the increase of mathematical errors made.

It has to be noted that research on more complex problems such as created by Electric Field Hockey software provided evidence of the instances of heavier-cognitive load being on nonspecific goal groups [27]. However, nonspecific goal group still developed more domain knowledge from the task than the goal-specific group.

A more recent study has confirmed Sweller's results. In that study the researchers have assigned a buoyancy related problem solving computer tasks to 233 15-years old students [28]. In addition to changing the specificity of the problem goal, problem learning goal specificity was also varied. The authors also found that non-specific learning goals imposed lower cognitive load on students and allowed students to use learning strategies.

III. Designing reduced-specificity physics problems

It is important to make the process of transformation of regular end-of-chapter problems into reduced-specificity problems as simple as possible to increase the likelihood of instructors creating and using such problems. In this section we describe our experience of creating such problems. This section contains two sample reduced-specificity problems as well.

In order to transform a regular goal-specific textbook problem into a reduced-specificity problem, firstly, decide if it is a transformational problem. If the textbook problem asks the solver to find the numerical values of more than one variable, then that problem can be easily transformed into a reduced-specificity problem by simply changing the task of the problem by making it the following:

"Find numerical values of as many variables or physical quantities as you can".

If the problems ask the solver to find a numerical value of only one variable, see if a numerical value of any other variable can be determined as well. If yes, then it can become a reduced-specificity problem with a similar modification.

We would recommend instructors to advise students to stay in the context of the course material and only to explore avenues related to what has been covered during the course in order to prevent instances of a student going off the topic and looking for values not related to the content material covered in the course. In our experience (we have used about 20 problems over 2 semesters) we haven't encountered such cases.

Although we did not hear complains from students for assigning reduced-specificity problems few students suggested that they would have been more comfortable if such problems specified the number of variables they should find. Thus, we would recommend for problems with more than one sub-component to specify approximately how many variables should be determined.

We present below an example of a regular problem that we transformed into a reduced-specificity problem.

Textbook problem: A student stands at the edge of the cliff and throws a stone horizontally over the edge with a speed 16.0 m/s. The cliff is 54.0 m above a flat, horizontal beach. (a) What are the components of the initial velocity? (b) How long after being released does the stone strike the beach below the cliff? (c) With what speed and angle of impact does the stone land?

The reduced-specificity version can be written as following:

Reduced-specificity problem: You are standing at the edge of the cliff and throw a stone horizontally over the edge with a speed 16.0 m/s. The cliff is 54.0 m above a flat, horizontal beach as shown on the figure below. Find values of as many variables or physical quantities as you can.

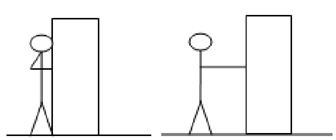
Rather than telling students which variables to find, the student has to determine himself or herself which variables can be determined and how. We believe students are more likely to start solving such problems by first trying to qualitatively analyze the situation and applying general equations of the physics topic (expert-like strategy) instead of starting problem solution by looking for a formula that contains the specific variable the problem is asking for without analyzing the situation (novice-like strategy).

Note that whenever possible we have chosen context-rich [29] problems or made additional modifications to make them such. Context rich problems have real-world context settings. To increase motivation, one can start problems with "You are…/you have been…" and then describe situations in such contexts that can motivate the solver to find an answer (e.g., start the problems with statements like: you have been hired as … and your job is…; you are watching TV about… and wonder…; etc). More suggestions on making problems context-rich can be found at [30].

Here is another reduced-specificity problem we have designed that has several sub-components and requires the solver to use more than one physics law or principle to get a complete solution:

Reduced-specificity problem: While standing firmly on the ground next to a refrigerator in your apartment, you push it with your palms with an average force of 650 N until your arms are fully stretched (you are doing it without bending your legs or making steps) as shown in the figure below. The mass of the refrigerator is 90 kg. The coefficient of kinetic friction between your shoes and the floor is 0.8, and the coefficient of kinetic friction between the refrigerator and the floor is 0.7. Find values of as many variables or physical quantities as you can.

HINT: Since you are the one pushing the refrigerator, you have to measure and incorporate your mass and the length of you arms into calculations.



Note the multitude of variables one can determine when solving this problem as well as the number of physics principles that can be applied. Firstly, students can determine numerical values of all the forces in the problem by applying Newton's laws. The accelerations of the student and refrigerator during the push can be determined from Newton's laws as well (assuming both slide; static coefficients of friction can be included in the problem as well). Once the accelerations are calculated, kinematics variables can be determined as well (displacements and final speeds at the end of the push and the duration of push). Then the solver can determine kinematics variables of the refrigerator's motion after the push (time of stopping and distance travelled after the push is over but before it finally comes to rest). If the problem is assigned after the chapters on energy and impulse-momentum are covered, students can also determine additional variables (e.g., kinetic energies, thermal energy, impulses and momenta).

It is possible to create reduced-specificity problems from more qualitative, non-transitional problems by making the task of the problem a "tell-all" problem. For example, give a situation and instead of asking for a specific quantity, ask "what can you determine about the problem situation using this information?" In our study we focused mainly on transforming the transitional problems into reduced-specificity problems.

IV. DESCRIPTION AND RESULTS OF THE STUDY

Course Description

The General Physics I (PH-201) course at QCC is an algebra-based 3 class hours and 2 laboratory hours course (4 credits). It is a first semester of a two semester-long introductory physics course with algebra prerequisite for engineering technology majors. QCC typically offers 4 lecture sections of the course with about 30 students in each section.

The first author (V. Shekoyan) was the lecture instructor for two sections; one section served as a control group and the other one as an experimental group.

The official textbook for the course was Serway & Vuille "College Physics". Weekly homework assignments consisted of end-of-chapter problems from the textbook in the control section and mixture of end-of-chapter and reduced-specificity problems in the experimental section). The course had three written midterm exams and one final exam. Midterm exams were composed of multiple-choice questions and open-ended problems. After collecting homework solutions were being posted on the course web-page. Students of both experimental and control groups had access to the posted solutions. A week after collecting homework solutions the instructor solved the homework problems in the lecture class as well. Note that the course did not have separate recitations at the time. About one-third of the lecture time was devoted to problem solving practice or review of homework problems.

Intervention

After the first midterm, the course instructor (V. Shekoyan) replaced some of the assigned homework problems in the experimental group with reduced-specificity problems that covered the same content. The difficulty level was taken into account during the replacement; if a lengthy reduced-specificity problem was introduced, it replaced commensurate number of regular problems that were assigned to the control section. Overall, seven reduced-specificity problems were assigned as homework problems

Two additional reduced-possibility problems were practiced by students in the experimental group during the lecture and then fully solved by the instructor after students' in-class solutions were collected.

All-in-all, both the experimental and control sections had the same lecture instructor, covered the same topics using the same textbook and similar homework assignments (except for the replaced reduced-specificity problems).

Student Sample

The experimental and control groups had 23 and 34 students, respectively. At the beginning of the semester we administered Mechanics Baseline Test [31] to determine the initial level of physics mastery of the two groups. The experimental and control groups were indistinguishable based on the baseline test (Table 1). The comparison of the grades on the first midterm (administered prior to the intervention; consisted of 10 multiple-choice and 3 open-ended problems) yielded the experimental and control groups as indistinguishable as well (Table 2). It was the first of 3 midterm tests administered during the semester at equal intervals. We utilized two-tailed unequal-variance t-tests comparisons for both baseline and midterm tests. Based on the comparison we can argue that prior to intervention the two groups were equivalent.

TABLE 1. Mechanics Baseline Pretest

T-test -> p=0.34	Control grp	Exp. grp
Number of subjects	N = 34	N = 23
Average grade	7.3/26	7.8/26
St. deviation	2.4	2.1

TABLE 2. First Midterm Exam scores

T-test -> p=0.15	Control grp	Exp. grp
Number of subjects	N = 34	N = 23
Average grade	19.9/40	22.3/40
St. deviation	7.6	6.5

Results and Discussion

We performed two-tailed unequal-variance t-test on the scores of both open-ended and multiple-choice sections of the final examination. The final exam contained 5 multiple-choice questions (focused mainly on conceptual understanding) and 3 open-ended problems similar to end-of-chapter standard problems. Note that all the midterm and final exam open-ended problems were goal-specific. It would have been unfair towards the control group to include reduced-specificity problems in the exams. The open-ended problems of the final exam are included in the Appendix.

The results of the test showed indistinguishable grades on the multiple-choice section of the final exam (with average score of 2.5/5 in both sections, p-value = 0.9). However, the total grades on the open-ended problems showed statistically significant higher scores in the experimental group (Table 3). Table 4 shows the analysis of the scores on Problem 1 of the final. It was the only problem directly related to the application of Newton's II law. Since the majority of the assigned reduced-goal specificity problems invoked the usage of Newton's II law, it is especially interesting to compare students' solutions on that problem. The experimental group's score was significantly higher than the score of the control group.

TABLE 3. Final Exam open-ended section total scores

T-test -> p=0.01	Control grp	Exp. grp
Number of subjects	N = 34	N = 23
Average grade	20.8/35	25.9/35
St. deviation	7.9	7.2

TABLE 4. Final Exam Problem 1 scores

T-test -> p=0.02	Control grp	Exp. grp
Number of subjects	N = 34	N = 23
Average grade	7.1/15	9.8/15
St. deviation	4	4.2

Final exam problem 2 was on momentum conservation law. The experimental group had been assigned only one reduced-specificity problem related to that topic. The comparison of the grades on that problem showed no difference between the two groups (Table 5). Final exam problem 3 required both understanding and applying ideas from both Newton's laws and work and energy. Experimental group had been assigned 2 problems related to the work and energy topics, and 5 out of 7 assigned reduced-specificity problems involved applying Newton's laws. Thus, we should expect some difference between the groups. The experimental group's average score on Problem 3 was significantly higher than the control group's score (Table 6).

TABLE 5. Final Exam Problem 2 scores

T-test -> p=0.7	Control grp	Exp. grp
Number of subjects	N = 34	N = 23
Average grade	8.2/10	8.5/10
St. deviation	2.5	2.3

TABLE 6. Final Exam Problem 3 scores

T-test -> p=0.03	Control grp	Exp. grp
Number of subjects	N = 34	N = 23
Average grade	5.9/10	7.7/10
St. deviation	2.9	2.6

We believe that the above results show a positive trend in student problem-solving outcomes. It is likely that the difference would have been higher if more reduced-specificity problems were used in the course. In future we would like to extend the number of subjects in our study. In addition to the pretest Mechanics Baseline Test and the midterm and final exams, we have also collected CLASS attitude and belief surveys [32] to investigate changes in students' attitudes and beliefs towards physics problem solving. We have also administered a modified version of Chi categorization tasks [33] in both experimental and control groups to measure student physics problem solving expertise (schema acquisition) levels. The analyses of the CLASS and categorization tasks are in progress.

In conclusion, in this preliminary study we have first time investigated the implications of using reduced goal-specificity problems in a physics classroom and noted that not only did it not hurt students' performance, but showed positive results. It was first time that the impact of reduced-specificity problem solving was evaluated in an "ecological environment", as an integral part of a science course in an actual classroom setting.

APPENDIX

Final exam open-ended problems

Problem 1: (15 points) A 10 000-gram object is lying on a horizontal surface. When you push it by 80 N horizontal force, it moves with acceleration 0.5 m/s/s.

a. (10 points) Find the coefficient of kinetic friction between the surface and the object.

b. (5 points) What would happen to the object if you were pushing it with 78.5 N horizontal force instead? Be as complete in your solution as possible.

Problem 2: (10 points) During a snowball fight two balls with masses of 0.4 and 0.6 kg, respectively, are thrown directly towards each other in such a manner that they meet head on and combine to form a single mass. The magnitude of initial velocity for each is 15 m/s. What is the speed of the 1-kg mass immediately after collision?

Problem 3: (10 points) You go to the gym 5 times a week, and each time you are there you bench press 80 kg thirty times. Each time you are lifting the barbell a distance equal to the length of your arm (about 0.8 m).

a. (5 points) Over the course of a year, estimate how much total work (in joules) you've done on the barbell while lifting it upwards (assume that you are lifting it with constant speed).

b. (5 points) If all of this energy were instead used to accelerate a tractor trailer (mass 20,000 kg) on a horizontal frictionless road, what speed would it attain (if you can't figure out how to do part a, make up a number for the energy, say 5 million joules and at least do this part)?

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