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The Worked-Example Effect and a Mastery Approach Goal Orientation

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Abstract: This study aimed to explore the impact of a mastery approach goal orientation (MAGO) on learning from worked examples. In this experiment (N = 98, mean age = 13.9 years), learners had their MAGO measured, and received instruction in mathematics, either through a worked-example or a problem-solving strategy. The study demonstrated that the worked-examples approach resulted in enhanced retention (but not transfer) and decreased cognitive load when compared to the problem-solving approach. However, there was a significant interaction between instructional strategy and the MAGO, indicating that only learners with a high MAGO benefited from worked examples. Learners with higher MAGO levels also experienced less cognitive load than learners with a lower MAGO. These results indicate a moderating role of MGO in enhancing the effectiveness of worked examples. This study also found that prior knowledge was the only factor influencing transfer performance, highlighting the importance of studying its impact.

Keywords: worked examples; cognitive load theory; mastery approach goal orientation

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1. Introduction

The *worked example effect* occurs when greater learning is achieved through studying worked-out solutions to problems rather than through problem-solving methods. The effect has been extensively researched within the field of cognitive load theory (CLT; see [1,2]), finding substantial evidence that for novice learners in particular, explicit instruction based on studying expert solutions to problems is more effective for acquiring new knowledge than unguided problem-solving methods (see [3,4]). Evidence supporting the worked example effect has been found in a wide spectrum of learning domains and under various conditions (for summaries, see [4,5]).

From the perspective of factors that moderate the worked-example effect, research has mainly focused on the impact of prior knowledge. When learners gain expertise in a domain, worked examples lose their effectiveness and can become equal or even inferior to problem solving. This phenomenon is known as the expertise reversal effect [6,7]). However, other individual differences that may moderate the effect have received less investigation. The main aim of the present research was to fill this gap and therefore broaden the worked-examples research by investigating the moderating impact of having a mastery goal orientation [8]. With few exceptions, notably studies by Belenky and Nokes-Malach [9,10], little research has been conducted that investigates worked examples combined with a mastery goal orientation.

2. Cognitive Load Theory and Worked Examples

According to cognitive load theory (CLT: see [5]), cognitive load is considered to be the working memory load expended during learning, and three categories have been identified ([1]). If the materials to be learnt involve many interacting elements, they are considered to be high in element interactivity ([11]) and generate *intrinsic cognitive load*. If the instructional materials are designed poorly, they can create *extraneous cognitive load*

by requiring learners to process information unrelated to learning. A third cognitive load (germane) has also been identified that corresponds to the mental resources invested directly in schema acquisition ([1]). In more recent studies, researchers have argued that germane load is not an independent load as such (see [12]). For example, Paas and van Merriënboer [13] define germane processing as the resources devoted to intrinsic cognitive load, and thus are dependent upon this load. Accordingly, total cognitive load is calculated by adding together intrinsic and extraneous loads only, rather than the three loads as previously defined (see [13,14]). Even though the concept of germane load has evolved over the years, CLT researchers have successfully designed instructional materials to accommodate the different types of cognitive load, especially in lowering extraneous cognitive load, in order to maximize learning ([1]).

Worked examples provide step-by-step solutions to a problem, and, according to CLT, allows the learner to devote more cognitive resources to learning about the problem domain than unguided problem solving [5]. In the case of learning through problem solving, learners may eventually solve the problem but not engage in schema acquisition due to a heavy cognitive load generated by inefficient problem-solving strategies [15]. Without domain-specific prior knowledge, a problem solver's limited working memory capacity becomes stretched to deal with both solving the problem and learning from it [2,4]. In contrast, worked examples provide the learner with a detailed expert problem-solving model [3,16], which reduces the negative effects of extraneous cognitive load while allowing for a more directed focus on learning and the subsequent generation of germane cognitive load.

Original CLT studies into the worked example effect were in the domain of mathematics [17,18]. But since this time, the worked-example effect has been found in a much broader range of learning domains, including non-scientific areas [4]. These diverse studies have consistently shown that worked examples leads to greater learning with lowered cognitive load. A number of additional learning strategies have also been successfully incorporated into the experimental designs, such as variability [19], collaboration [20,21], fading strategies [22], process explanations [23], isolating elements [24], individual solution steps [25], and self-explanations [26]. These studies have shown that other learning strategies can be successfully incorporated into worked-examples to enhance their influence further. Research has also identified a number of factors that moderate the effectiveness of worked examples.

Moderating Factors of the Worked Example Effect

As described in the previous section, the worked example effect has been identified in many learning domains; however, its effectiveness is highly dependent upon the learner's relevant prior knowledge. For learners with high prior knowledge, worked examples have been found to be less effective, in contrast to learners with low prior knowledge whom benefit most from them. This phenomenon has been called the *expertise reversal effect* [6]. Learners with high levels of prior-knowledge do not need step-by-step instructions, which they can find redundant, leading to increases in extraneous cognitive load and reduced learning [27], whereas high-knowledge learners can benefit from fewer guided instructions such as that provided by problem-solving strategies [7] due to enhanced domain-specific working memory capacity, which allows learners to cope and benefit from the higher cognitive demands of problem solving [2,4]. It is domain-specific knowledge that makes the difference, rather than more general working-memory capacity (see [28]).

In addition to prior knowledge, a recent meta-analysis by Barbieri et al. [29] found the correctness of examples, timing of administration (practice or skill acquisition), and the use of self-explanation prompts to be moderating factors, whereas these factors were significant moderators and were implemented by the study designers, and were not necessarily dependent upon individual characteristics per se.

Although not exhaustive, the above section describes some of the factors that moderate the worked example effect, although few can be considered to be individual traits. However,

of interest to the present study is the finding that a mastery goal orientation—an individual motivational trait—has a potential moderating effect [9,10]. Before describing this research, some theoretical background is provided on goal orientation theory.

3. Goal Orientation Theory

Goal orientation theory is part of the broader field of motivation, which has been shown to be a crucial factor in effective learning (see [30–32]). Motivational theories are commonly used to explain student engagement, persistence, and performance. According to early goal orientation theory, a learner can either hold a mastery goal orientation (sometimes referred to as a learning goal orientation) or a performance goal orientation (see [8,33]). A mastery goal oriented (MAGO) learner aims to increase competence and has a desire to learn. A performance goal oriented (PGO) learner aims to prove their competence and has a desire to display their competence compared to others [34]. However, achievement goal orientation is now commonly recognised as consisting of four distinct achievement goals as a 2 × 2 framework: mastery approach, mastery avoidance, performance approach, and performance avoidance [35,36].

Studies examining the links between achievement goal orientation and achievement have found that a MAGO has been frequently viewed as the ideal goal orientation (see [37]). Individuals who have a MAGO have been found to be more enthusiastic about learning and more cognitively engaged [38]. Furthermore, Lee et al. [39] found that a MAGO can be associated with a greater working memory capacity in learning mathematics. However, some studies (see [40]) have failed to find a positive relationship between a MAGO and learning.

In contrast to a MAGO, a PGO has often been correlated with low academic achievement. Lee et al. [41] examined personality characteristics from self-determination theory and its influence on performance and levels of enjoyment based on achievement goal levels from university undergraduate students. Lee et al. [41] found mastery and performance approach goal orientation facilitated focus by focusing on a positive mindset. In addition, PGO learners have been found to withdraw from tasks when faced with the possibility of failure, show little interest in difficult tasks, and have the tendency to choose less challenging materials to increase their possibility of success [41]. However, research findings into PGO have also been inconsistent. For example, Elliot et al. [35] examined achievement goal orientation as predictors of study strategies and tested the study strategies as mediators between achievement goal orientation and exam performance on undergraduate students. They found a PGO to be positive predictors of surface processing, persistence, exam performance, and were not significantly associated with any study strategies; and mastery goals were positive predictors of deep processing and persistence, and were unrelated to surface processing and disorganisation.

Pintrich [42] investigated the role of mastery and performance goals and their associations with motivation, affect, strategy utilization, and academic performance among junior high school students. The results revealed that students who had both high mastery goal orientation and high performance goal orientation demonstrated an increased use of cognitive strategies for learning. Contrary to initial expectations, significant differences in anxiety, self-handicapping, and risk taking were not associated between students exhibiting high levels of both mastery goal orientation and performance goal orientation. However, it was noteworthy that the students with both high mastery goal orientation and performance goal orientation exhibited higher perception of task value, including perceived utility and significance of mathematics, compared to students who were high mastery goal orientation and low performance goal orientation.

3.1. Research Combining CLT and Mastery Goal Orientation

The present study focuses on only one aspect of achievement goal orientation theory: Mastery Approach Goal Orientation (MAGO) and how it impacts cognitive load. Some limited studies have investigated this relationship specifically. For example, a study by

Steele-Johnson et al. [43] found that a MAGO had beneficial effects on tasks with high cognitive load, whereas a performance-based orientation benefitted more from low cognitive load tasks. Cook et al. [44] found that in a medical simulation training activity, a MAGO was positively correlated with germane cognitive load. In other words, this goal orientation led to more mental effort applied to knowledge acquisition.

Studies into worked examples and goal orientations have also received some research interest. For example, Crippen et al. [45], using worked examples in a web-based learning study, found that although a MAGO was the best predictor of performance, it was not related to how often students used worked examples when given a choice. In contrast, a PGO was positively related to the use of worked examples. It was argued that students with a PGO preferred simpler tasks (as provided by worked examples), which enabled them to gain confidence through perceived lower cognitive load and allowed them to demonstrate success. For MAGO students, it was argued that they may not engage with worked examples if they believed that they would not lead to deeper understanding.

A small number of studies have examined the impact of goal orientations on learning from both worked examples and problem-solving strategies. A study by Belenky and Nokes-Malach [46] investigated goal orientations when comparing a *tell-and-practice* instructional approach (a type of worked examples) with an invention approach (a type of problem solving) on transfer outcomes. They also investigated the impact of an additional worked example imbedded in a test prior to a transfer task. They found that regardless of the original instructional format, the single worked example located before the transfer task enabled the task to be solved more easily than without a worked example. They also found that tell-and-practice (initial worked examples) instruction led to better procedural skill, but invention (problem solving) led to better transfer regardless of orientation (mastery or performance). However, an initial MAGO was required for successful transfer using the initial tell-and-practice approach.

A later study by Belenky and Nokes-Malach [9] also found that regardless of the original instructional format, the single worked example before a transfer task enabled the task to be solved more easily than without a worked example. In addition, students with a MAGO benefitted more from the worked example than a PGO. Evidence also emerged that the problem-solving instruction (invention) led to greater understanding and care about their answers than the worked example instruction. Students with high mastery levels had success with transfer regardless of instruction, whereas those with low mastery levels benefited more from an invention approach. It was argued that the problem-solving instruction led to the adoption of mastery-type goals and greater conceptual understanding, whereas the worked examples led to less attention on conceptual understanding due to a focus on the repetition of the non-transfer tasks. A further study by Belenky and Nokes-Malach [10] found that only a MAGO predicted transfer performance compared to the structure and framing of the learning tasks.

In terms of the benefits of worked examples and problem-solving methods, the findings reported in the previous section are somewhat mixed, but nevertheless indicate that a learner's goal orientation has been linked to the outcomes of both worked examples and problem solving. Hence, there is a strong motivation for investigating this topic further using a cognitive load theory framework.

3.2. The Current Study

The current study extends the research into worked examples by investigating how a mastery approach goal orientation interacts with the worked example effect. Previous research by Belenky and Nokes-Malach [9,10] into this topic used a sparse number of worked examples embedded in the tasks, whereas the present study uses a full set of worked examples during instruction consistent with most CLT studies (see [5]). Furthermore, both retention and transfer problems were investigated, as well as a measure of cognitive load. A further difference was that the previously noted studies did not measure prior knowledge in this domain, which we included to ensure that its overall impact would be investigated.

Mathematics, specifically algebra, was chosen as the learning topic, as it was expected to generate a worked-example effect, based on previous research (see [17,18,47]), and importantly has high element interactivity [11], with an expected medium level effect size (see the meta-analysis of Bichler et al. [28]).

3.3. Study Hypotheses

A number of measures were collected in the study. Participants completed a pre-test to assess *prior-knowledge*, a post-test to measure *retention* of the information, and a *transfer* test to see if the knowledge gained could be applied to more complex tasks. A difficulty-rating measure was collected to gain an assessment (index) of cognitive load (see [48–50]). Participants were also measured for their MAGO using a three-item scale based on Elliot and Murayama's survey [51].

Based on the literature outlined above, a number of hypotheses were formulated. Firstly, the extensive research into worked examples indicates that for novice learners in particular, worked examples lead to greater retention of information with reduced cognitive load compared to problem solving. Regarding transfer, even though there are studies that have shown that problem-solving strategies such as invention (see [9]) can lead to transfer success, the majority of studies into CLT have found that worked examples leads to greater transfer than problem solving (see [5]). Therefore, it was predicted that:

Hypothesis 1. *Worked examples compared to problem solving would lead to greater (a) retention, (b) transfer, and (c) lower cognitive load.*

Regarding a MAGO, the evidence reported above suggests that having a MAGO is correlated with successful learning [52], including transfer [9,10] as well as motivation [53]. Hence, it was predicted that:

Hypothesis 2. *A high compared to a low MAGO would lead to greater (a) retention, (b) transfer, and (c) lower cognitive load.*

Of great interest were the possible interactions between worked examples and a mastery goal orientation. Due to limited studies in this domain and conflicting findings, no specific hypotheses were made, but were investigated as an open research question:

To what extent is the worked example effect moderated by a mastery goal orientation?

4. Method

4.1. Participants

Ninety-eight grade-9 boys (mean age of 13.9 years) from a high school in Sydney participated in the experiment. These participants were randomly allocated into one of two experimental groups: worked examples (n = 50) or problem solving (n = 48).

4.2. Materials

Study phases. The experiment consisted of 4 phases: a MAGO survey, a prior knowledge test (pre-test), an acquisition phase, and a test phase (post-test and transfer).

The MAGO survey. At the start of the experiment, participants were given three items from the Achievement Goal Orientation-Revised (AGO-R) questionnaire to measure their mastery approach goal orientation [51]. It should be noted that it is quite common to use parts of a more comprehensive survey to examine specific variables such as a MAGO (see [54,55]). The 3 items were modified to focus specifically on mathematics. For example, the item "My aim is to completely master the material presented in this class" was modified to "My aim is to completely master mathematics". The three items were finalised as:

(1) My aim is to completely master mathematics.
(2) My goal was to learn mathematics as much as possible.
(3) I am striving to understand the content of mathematics as thoroughly as possible.

Each item was scored on a 5-point Likert scale ranging from Strongly Disagree (-2) to Strongly Agree (2). The 3 ratings were added together to give a final score ranging from a possible minimum of -6 to a maximum of 6. A Cronbach alpha score was 0.70, indicating an acceptable degree of reliability [56].

Pre-test. To test for prior knowledge, a pre-test was conducted consisting of a set of six algebra problems of an advanced nature for the age group. Each problem contained one unknown variable that had to be calculated (e.g., see Figure 1). The solutions involved substitution and the re-arrangement of the formula, and other algebraic transformations. There were three types of problems. The first problem type was an algebra question that required the participants to understand the square root function applied to an algebraic function (e.g., $\sqrt{\frac{x}{5}}$). The second type of problem required an understanding of an algebraic cubic power (i.e., x^3). The final type of problem required an understanding of algebraic fractions (e.g., $\frac{x}{1-b}$). The pre-test consisted of 2 questions of each type, and was presented on A4 sheets of paper.

Study the follow problem	**Solve** the following problem
Find x, $if \quad y = 4$ and $z = 3$	Find a, $if \quad b = 4$ and $c = 5$
Where $y = z\sqrt{\frac{x}{5}}$	Where $b = c\sqrt{\frac{a}{4}}$
Working	
$y = z\sqrt{\frac{x}{5}}$	
$4 = 3\sqrt{\frac{x}{5}}$	
$\frac{4}{3} = \sqrt{\frac{x}{5}}$	
$\frac{16}{9} = \frac{x}{5}$	
$\frac{80}{9} = x$	
$\therefore x = \frac{80}{9}$	

Figure 1. A worked example problem pair.

Using a pre-test enabled us to screen for students with high prior knowledge, which might have led to expertise-reversal effects by reducing the effectiveness of worked examples [6] The low scores on this test (see the Section 5) indicated that, overall, students had low prior knowledge in this domain, and no individual was excluded.

Acquisition phase. All participants were required to learn about the algebra topic either using worked examples or by being left to their own problem-solving strategies. The worked-example instrument consisted of 6 problem pairs, consisting of 6 step-by-step solutions and 6 similar problems to solve. The use of problem pairs in this fashion has been shown to be a highly effective way of using worked examples (see [5]). Using this format, participants were required to study a worked example and then solve a similar problem immediately. Figure 1 provides an example of a problem pair that was presented on a single sheet of A4 paper. The only difference between each of the worked examples

and the corresponding problem to be solved were the variable terms (e.g., y or b) and the numbers to be substituted into the variables.

The problem-solving material consisted of the 12 identical problems used in the worked examples material, except the 6 step-by-step solutions that were provided in the worked examples material that were not provided in the problem-solving material. Therefore, these participants were required to solve all twelve algebra questions without any guidance. However, both groups were provided with final answers (but no solution steps) to all problems that participants were required to solve themselves without guidance. Hence, some feedback was provided, as the participants' answers could be checked.

Test phase. The test phase consisted of a *post-test*, which had six problems identical to the pre-test, and a *transfer* test consisting of six questions. The six transfer questions were also algebraic in nature, but more complex than the post-test questions, involving more variables to be manipulated.

Cognitive load measure. To measure cognitive load following the acquisition phase, a single-item difficulty scale was constructed. Participants were asked to indicate the level of perceived difficulty experienced during this learning phase using a 9-point Likert scale, consisting of: "extremely easy (1), very easy (2), fairly easy (3), slightly easy (4), neither easy or difficult (5), slightly difficult (6), fairly difficult (7), very difficult (8), and extremely difficult (9)". This scale was a modified version of the original Paas scale (see [49]), which used a 9-point scale based on mental effort. Both difficulty and mental effort have been used extensively in cognitive load theory research to obtain a reliable index of cognitive load (see [48,50]).

4.3. Procedure

After an introduction explaining the purpose and format of the study, participants were given the MAGO survey to complete on a single sheet of paper (3 min). Secondly, they were given the prior knowledge pre-test for a maximum of 10 min. Participants were then given 30 min for the acquisition phase. Once the participants completed the acquisition materials, they were instructed to indicate the level of perceived difficulty experienced. Finally, they were given 20 min for the test phase. All phases were completed in a single session of about 70 min. After each phase, all materials and responses were collected.

4.4. Scoring of the Tests

The pre-test and post-test were identical, consisting of 6 problems to be solved. For each correct answer, 2 marks were awarded, giving a maximum score of 12 marks for these tests. Similarly, for the 6 transfer questions, a maximum score of 2 was awarded for each problem, resulting in a maximum score of 12. A number of partial marks were awarded for final incorrect answers on all tests that contained some correct steps, such as successful substitution and algebraic transformation, according to a strict marking rubric. Two experienced researchers graded all student answers, and when differences arose, they were resolved in order to reach full agreement. Cronbach alpha scores on the pre-test, post-test, and transfer test were 0.79, 0.90, and 0.87, respectively, indicating a high degree of reliability.

5. Results

5.1. Improvements in Learning from Pre-Test to Post-Test

To investigate whether learning occurred from pre-test to post-test, which were identical, *t*-tests were conducted on the combined worked examples and problem-solving groupings. A significant improvement was found in the worked examples group from the pre-test (M = 2.21, SD = 2.13) to the post-test (M = 4.90, SD = 3.90): t (50) = 56.45, $p \leq 0.01$, d = 0.90. The problem-solving group also improved from pre-test (M = 1.94, SD = 1.81) to post-test (M = 2.89, SD = 2.38), t (47) = 12.17, $p < 0.01$, d = 0.45. Thus, both strategies resulted in learning gains.

5.2. Regression Analyses

To test the hypotheses, stepwise linear regression was used to analyse the data for each dependent variable (retention test, transfer, and cognitive load measures). Potential predictors included prior knowledge (pre-test), mastery level, learning strategy (worked example vs. problem solving), and all interactions. Examination of correlational data and initial regression analysis revealed a number of significant predictors across the different measures, as reported below. In the following analyses, R^2 represents the explained variance by Step 1, ΔR^2 represents the change in variance on subsequent steps, and β represents the standardized coefficients.

Retention test. For the retention post-test, a two-factor model was identified where prior knowledge ($\beta = 0.68$, $p < 0.001$, $R^2 = 0.49$) and the mastery–worked examples interaction ($\beta = 0.25$, $p < 0.001$, $\Delta R^2 = 0.06$) were found to be significant (Table 1). To investigate this interaction, analyses were conducted by splitting participants into two groups based on the median mastery scores. Scores for the Low MAGO group ranged from −1 to 3, and the High MAGO group ranged from 4.0 to 6.5.

Table 1. Descriptive statistics and intercorrelations among variables of retention scores.

Variable	*n*	*M*	*SD*	Variable		
				1	**2**	**3**
Retention test	98	3.86	3.34	-		
Prior knowledge	98	2.032	1.94	0.000 **	-	
Mastery Approach Goal orientation	98	3.28	1.89	0.006	0.002	-
Mastery Approach × Worked Examples	98	4.97	1.66	0.002	0.320	0.214 **

Note: ** $p < 0.001$.

Clearly, prior knowledge impacted on each condition, and therefore it was used as a covariate to control for its impact. Hence, a 2 (mastery levels) × 2 (Worked examples vs. problem solving) ANCOVA was conducted: F (1, 57) = 7.16, $p = 0.01$, $\eta_p^2 = 0.11$. Simple effects tests revealed a significant difference in the higher MAGO group, F(1, 25) = 8.60, $p = 0.01$, $\eta_p^2 = 0.26$, where the worked examples group ($M = 4.69$, $SE = 3.68$) outperformed the problem solving group ($M = 1.50$, $SE = 1.49$). There was no significant difference in the low MAGO group, $F < 1$, whereas the worked-example group ($M = 2.06$, $SE = 1.78$) scored less than the problem-solving group ($M = 2.59$, $SE = 1.39$), but not significantly.

Cognitive load measure. For the cognitive load measures, a three-factor model was identified where prior knowledge, ($\beta = -0.36$ $p < 0.001$, $R^2 = 0.21$), mastery–worked examples interaction ($\beta = -0.3.7$, $p < 0.001$, $\Delta R^2 = 0.14$), and mastery levels ($\beta = -0.25$, $p < 0.01$, $\Delta R^2 = 0.07$) were found to be significant factors (Table 2). The negative β-values indicated that high prior knowledge and a high mastery level led to reduced cognitive load.

Table 2. Descriptive statistics and intercorrelations among variables of cognitive load measure.

Variable	*n*	*M*	*SD*	Variable		
				1	**2**	**3**
Cognitive Load	98	7.51	2.00	-		
Prior knowledge	98	2.032	1.94	0.000 **	-	
Mastery Approach Goal orientation	98	3.28	1.89	0.000	0.002 *	-
Mastery Approach × Worked Examples	98	4.97	1.66	0.000	0.320	0.214 **

Note: * $p < 0.01$, ** $p < 0.001$.

The mastery–worked examples interaction was investigated further with an ANCOVA, using the same format as applied to the Retention analysis. For the high MAGO, there was a significant effect: F (1, 45) = 12.90, $p < 0.01$, $\eta_p^2 = 0.22$, with the combined problem-solving groups reporting higher levels of difficulty (M = 8.00, SE = 0.42) than the worked example groups (M = 5.86, SE = 0.41). A significant main effect was also found for the low MAGO group, F (1, 47) = 11.78, $p < 0.01$, $\eta_p^2 = 0.20$, with the problem-solving group (M = 8.60, SE = 0.20) reporting higher levels of difficulty than the worked-example group (M = 7.62, SE = 0.20). For both mastery groups, problem solving led to greater cognitive load, as measured through the difficulty scale, compared to worked examples. However, this interaction was caused by a larger worked-example advantage (lower cognitive load) for the high MAGO group, as shown by the differences in the group means reported above.

Transfer test. For the transfer test, a one-factor model was identified, with only prior knowledge as a significant predictor ($\beta = 0.43$, $p < 0.001$, $R^2 = 0.65$).

Relationship between MAGO scores and prior knowledge. A significant correlation was found between MAGO and prior knowledge (r = 0.29 $p < 0.01$), which is consistent with previous research showing this relationship (see [57]).

5.3. Testing the Hypotheses

Hypothesis 1a predicted a worked-example effect, in that worked examples would be superior to problem solving for retention problems. This was partially confirmed in that the worked-example effect was moderated by MAGO levels. A worked-example effect was found only for learners with the higher level of MAGO, but not the lower level. Hypotheses 1c was confirmed, as, overall, worked examples reduced cognitive load, as measured through the difficulty scale, although the effect was more pronounced at the higher MAGO level. Hypothesis 1b was not supported, as the only influence on the transfer problems was prior knowledge. Hypothesis 2a and 2b predicted a higher MAGO would lead to greater retention and transfer, but both of these predictions were not supported. However, participants with a higher MAGO experienced less cognitive load during instruction.

6. General Discussion

An aim of the study was to use learning content that would lead to a worked example effect. This aim was partially achieved, as participants with high levels of mastery whom learned from worked examples scored higher on retention problems than those who followed their own problem-solving strategies during the acquisition phase. This result is consistent with the worked-examples effect (see [4]). However, the interaction between mastery levels and the use of worked examples is the most significant and novel finding in this study. Learners with high MAGO levels benefited most from worked examples compared to problem solving than learners with lower MAGO levels. It may be that high MAGO learners had a greater desire to engage in worked examples consistent with a desire to master the materials (see [37,38]), and may view worked examples as the superior learning strategy. Furthermore, the worked-examples strategy of "study a solution to a problem, then solve a similar one", originally devised by Sweller and Cooper [18] for motivational purposes (even though they never tested this assumption), may have a further positive effect on MAGO learners, whereas other formats of worked examples have been successfully used from a learning perspective (see [58]), but they have not been compared from a motivational perspective. Hence, a research avenue could further investigate the link between motivation and a worked-example format.

This interaction is also interesting because it does not mirror the usual results relating to expertise. The expertise reversal effect dictates that as expertise in the domain increases, worked examples lose their effectiveness [6]. However, the high MAGO learners were found to have higher levels of prior knowledge, as measured in the pre-test, than those with lower mastery levels, but no expertise reversal effect was found. In fact, an opposite effect of a reversal was found. It was notable that, in this study, prior knowledge of all participants combined was very low (mean = 2.0 from a maximum of 12 on the pre-test), suggesting

that perhaps a minimum level of prior knowledge is required for worked examples to have the most impact.

The study found that worked examples did not lead to a direct advantage on the transfer test. The only factor impacting on transfer in this study was prior knowledge, suggesting that the interventions did not increase prior knowledge sufficiently to make a significant impact. Previous research [9,10,46] into mastery orientations and worked examples has not included prior-knowledge measures, and therefore the present study extends their research further by including this factor, but also demonstrates how critical it is to include it. The early research into worked examples (see [17]) found that a significant amount of exposure to worked examples was needed to achieve the required automation of fundamental knowledge and skills that lead to transfer effects (see also [58,59]). Hence, a greater intervention period in this study may have been needed to promote transfer.

There are also a number of other potential explanations into why worked examples did not promote transfer. Belenky and Nokes-Malach [9] suggested that worked examples may fail to promote transfer because learners may pay less attention to conceptual understanding due to a focus on repetition of the non-transfer tasks. Although learners who initially had to learn through problem solving also did not show transfer advantages, some previous studies had found that problem-solving strategies, such as invention (see [9]), can lead to transfer. However, facilitating the development of invention through specific activities, even though it is a form of problem solving, is very different to the totally non-directed problem solving used here. Furthermore, some of the best results for invention activities were obtained in conjunction with a worked example (see [9]). Hence, more directed problem solving strategies (see [60]), as well as greater time [59], may be required to bridge the prior knowledge gap for transfer improvements in this domain.

Furthermore, Schwartz and colleagues [61,62] suggest two views of transfer: one as the direct application of previously learned knowledge to a problem question, and the other as the preparation for future learning. In our study, the direct application of previously learned procedural and conceptual knowledge was needed to answer the transfer question. Similarly to our study, several studies have also reported no transfer or mixed results (see [48]). Clearly, further research is required to test these possible explanations into a lack of transfer effects.

Regarding mastery effects, having a high MAGO did not lead to greater test scores than those with lower MAGO levels. Although a high MAGO has been frequently associated with higher achievement (see [52]), some research (see [40]) has also failed to find a positive relationship between MAGO and academic performance. However, a high MAGO did lower cognitive load during instruction. This may be due to high MAGO learners having a greater working memory capacity, as proposed by [41], as well as a desire to be more cognitively engaged in learning (see [38]).

Study Limitations

Firstly, only males were used in the study. Males who have extrinsic motivation tend to perform poorly with a lack of self-regulation (see [63]) and are less likely than girls to hold mastery goal orientations [64]. Therefore, further studies need to include females to see if the results are replicated.

Secondly, it is worth noting that we used the exact same pre-test and post-test. Hence, each group had more experience of problem solving during the pre-test, which could have led to pre-instruction learning. However, there is no evidence that this impacted on the overall results, as the predicted worked-example effect occurred. Future research might consider using a different test.

Thirdly, we focused only on a mastery goal orientation. Achievement goal orientation research also includes a performance goal orientation, as well as individual desires to 'approach' the desired state or 'avoid' the undesired state ([36]). Hence, future research could also include scales to gain more insights into the cognitive processes at work in similar instructional environments.

Fourthly, we used a single measure of cognitive load (difficulty scale) based on the original Paas scale [49]. Whereas this has been used successfully in multiple CLT studies [48,50], it is a perceived level of difficulty and corresponds to an index of total cognitive load only. Hence, future research in this domain could measure individual cognitive loads aligning with intrinsic, germane, and extraneous loads (see [65]), which could provide more insights.

7. Conclusions

There were some novel directions taken in this study. Little research has been conducted that combines worked examples with goal orientation theory. The present study used a learning environment that combined classical worked-example designs that feature the alternation of a worked example with a similar problem to solve (see [4]). As expected, compared to problem solving, worked examples showed a number of advantages, including superior retention of information and lowered cognitive load during instruction. However, the retention learning advantage was confined to learners with high mastery levels only. This finding that only MAGO learners were motivated with a desire to improve and master skills within the worked-example framework is, as far as we know, a unique finding, demonstrating that investigating the impact of goal orientations on worked examples and problem-solving strategies has great potential and is worthy of further research. Judging by these initial findings, such research could potentially identify a new CLT effect: A *mastery goal worked-example effect*. Furthermore, this research has extended a recent trend to combine CLT research with motivational aspects (see [53,55,66,67]), which opens up new avenues for research that can help in understanding how to design materials to enhance learning and instruction. Interactions between CLT and motivation have been rarely studied until more recent times. The aim of the present study was to continue this recent trend by investigating how learners with a mastery achievement goal orientation (see [8]) respond to learning from worked examples and problem solving [17]. Furthermore, the study also demonstrated the importance of prior knowledge to new learning scenarios, as it had the largest impact on all the measures collected, especially transfer.

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