Impact of Guidance on the Problem-Solving Efforts of Instructional Design Novices

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This exploratory study examined differences in the problem representations of a case-based situation by expert and novice instructional designers. The experts and half of the novices (control group) received identical directions for case analysis, while the other novices (treatment group) received additional guidelines recommending analysis strategies that experts tend to use. After participants' case analyses were scored on four dimensions of problem representation, a Wilcoxon nonparametric test was performed. Significant differences were noted between experts and control novices on the total score and on two dimensions of problem representation. Treatment novices did not differ significantly from experts, while control and treatment novices differed significantly on one dimension. Implications for future research and practice are discussed.

In general, expert problem solvers differ from novices in that they possess deep and connected domain knowledge that allows them to identify meaningful patterns in a problem situation (Bransford, Brown, & Cocking, 2000). In the instructional design (ID) domain, this expertise is manifested in a designer's ability to produce meaningful problem representations by integrating information in a given situation with his or her prior knowledge and experience (Ertmer et al., 2008; Rowland, 1992). That is, ID experts tend to explain problem situations in terms of underlying principles and to make connections between the different aspects of the situation. Novice designers tend to focus on surface features while failing to establish connections among the different issues (Ertmer & Stepich, 2005).

Instructional Design Expertise

Ertmer and Stepich (2005) defined an ID expert as a "solver" of ill-defined problems. Ill-defined, or ill-structured, problems are "those that we encounter in everyday life, in which one or several aspects of the situation is not well specified, the goals are unclear, and there is insufficient information to solve them" (Ge & Land, 2004, p. 5). Eseryel (2006) described ID problems as "archetypal" (p. 11) examples of ill-structured problems in that they typically require designers to understand, simultaneously, the specifics of a given situation (e.g., context, learners, tasks) as well as the multiple components of the larger system in which they are embedded (e.g., project constraints, relevant technologies, multifaceted learning goals). Often, problem-solving

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efforts are confounded by designers' limited knowledge of the specific problem domain (Ge, Chen, & Davis, 2005). This is particularly true of novice designers.

Rowland (1992) found that the mental processes that experts and novices use were significantly different when they were asked to solve an ID problem. First, novices did not see the problem as being ill-structured and thus assumed that the information and variables were clearly specified. Second, they did not think beyond the written description of the problem, concentrating primarily on the content of the instructional materials provided. Finally, they shifted rapidly from problem analysis to solution generation and failed to elaborate solution alternatives. Experts were able to activate mental models that connected relevant previous experiences with domain-specific knowledge and skills, thereby activating a mental framework for representing the problem and seeking a solution. Furthermore, based on their conceptual understandings, experts integrated given information with prior knowledge and experiences to make inferences that went beyond the stated information. Experts spent significant time analyzing the problem and moved to solution generation only after ensuring that they understood the situation completely.

Supporting Novices' Problem-Solving Efforts

The increasing need for preparing highly skilled and competent ID professionals (Richey, Fields, & Foxon, 2001) has led to the increased adoption and use of instructional methods that emphasize real-world problem solving (Dijkstra, 2005; Jonassen & Hernandez-Serrano, 2002). However, research has demonstrated that simply engaging students in problem solving does not ensure the development of expertise (Dufresne, Gerace, Hardiman, & Mestre, 1992). According to Kirschner, Sweller, and Clark (2006), "knowledge organization and schema acquisition are more important for the development of expertise than the use of particular methods of problem solving" (p. 83). Taconis, Ferguson-Hessler, and Broekkamp (2001) proposed that problem-solving skills are developed through a combined focus on building a problem schema and using effective learning strategies. Sweller (1988) argued that the traditional means-end approach to problem solving, mostly used by novices, is ineffective because learners' efforts to solve the problem compete with their abilities to acquire schemas due to the limited capacity of working memory. To address this difficulty, Kirschner et al. (2006) proposed guidance as a key strategy for helping novices acquire problem-solving skills, primarily because it reduces cognitive load. According to Dufresne et al. (1992), "Helping novices acquire schemata will necessitate shifting novices' attention away from means-ends analysis and toward problem-solving approaches that highlight the use of principles, concepts, and procedures" (p. 310). External supports that can aid in the development of knowledge structures include modeling (Schoenfeld, 1985), peer questioning (King, 1991), and question prompts (Scardamalia, Bereiter, & Steinbach, 1984).

The importance of guidance for the development of problem-solving skills is receiving increased attention in the ID field (Ertmer et al., 2008). Given that, in contrast to experts, novices spend very little time defining the problem (Ge et al., 2005; Ge & Land, 2004; LeMaistre, 1998; Rowland, 1992), it appears necessary to guide novices in ways that help them consider the underlying structure of the problem. Ertmer and Stepich (2005) outlined four dimensions of the problem-solving process that relate to problem definition or representation. These include the ability to (1) articulate a coherent representation of the situation, (2) interpret available information in terms of underlying principles, (3) describe relationships among identified issues, and (4) reflect on, and make inferences about, the situation based on what they know.

Rowland (1992) recommended the design of a tool, incorporating aspects of ID expertise, as a potential strategy for helping novices solve ill-structured problems in more expert-like ways. This tool might involve something as simple as a checklist or comprise a sophisticated expert system. Primarily, the tool would be designed to engage novices in deeper analysis and understanding of the macrosystem in which the problem and possible interventions were embedded. In support of this idea, Ge et al. (2005) found that a combination of question prompts, expert guidance, and peer feedback improved novices' problem-solving skills. Dufresne et al. (1992) reported that novice physics students could be directed to focus on the deep structure of problems by instituting "constraints" that forced them to attend to the underlying principles and concepts during problem analysis. The current exploratory study was designed to build on and apply these ideas within the ID field by posing two questions:

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- How do the problem representations of ID experts and novices compare?
- What is the effect of guidance (in the form of analysis guidelines) on novices' problem representations?

Method

Research Design

We used a posttest-only control group design, with counterbalanced assignment, to compare the problem representations of novices and experts and examine the impact of analysis guidelines on novices' problem representations. The analysis guidelines constituted the independent variable and the case analyses of the participants served as the dependent variable. The data were collected from 24 novices and 8 experts who agreed to participate and provide a case analysis for the given problem.

Role of the Researcher

The research study began as part of an advanced educational technology research course at a large midwestern university and continued after the

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course was over. The research team consisted of nine graduate students, their professor, and a professor from a large western university who served in an advisory role. Graduate students differed with regard to gender (five female and four male), nationality (four Americans and five international), major (six educational technology majors and three other majors), and degree program (five doctoral students and four master's students). All researchers completed the required Institutional Review Board training and were certified to conduct the study.

Researchers collaborated during weekly class meetings and via e-mail and online discussions while defining, planning, and implementing the study. Based on researchers' backgrounds and availability, tasks (e.g., construction of the demographic survey) were completed by the whole group or by subgroups. Tasks completed by subgroups were made available to the other researchers for review and suggestions.

Selection and Description of Participants

Categorizing an individual's level of expertise, a priori, is a challenge. One reason that a large amount of expert-novice research has been done with chess players is that chess organizations have developed sophisticated scales for evaluating expertise based on performance in tournaments (Gobet & Charness, 2006). Unfortunately, a similar scale for "grading" practitioners does not exist for instructional designers. As a result, ID researchers have used two primary categorization methods: years of experience (LeMaistre, 1998; Perez & Emery, 1995) and nominations from others (Korth, 1997; Rowland, 1992).

For the purposes of this study, years of experience were used to distinguish expert from novice instructional designers. Experts were defined as individuals who were currently working as instructional designers, had completed one or more postgraduate ID courses, and had a minimum of 8 years of practical experience. Novices were defined as individuals who had completed no more than one postgraduate ID course and had no more than 3 years of practical experience as an instructional designer. No effort was made to assess the skill levels of the participants or the types of ID problems on which they had worked previously. However, the criteria applied allowed us to determine that the participants were sufficiently knowledgeable about ID to complete the case analysis task and created a gap in experience that was wide enough for meaningful comparisons between the groups.

Novice participants were solicited using two educational technology listservs and at the end of three introductory ID courses taught at the authors' institutions. Experts were solicited from among graduates of the researchers' institutions. In total, 24 novices and 8 experts agreed to participate in the study. Each participant was directed to an online demographic survey to collect additional information related to their educational backgrounds, previous ID experiences, and confidence in solving ID problems (see Tables 1 and 2). Respondents who did not meet the criteria of having 8 or more years of ID experience (experts) or 3 or fewer years (novices) were not allowed to participate.

TABLE 1
Demographics for Participants

	Treatment	Control	Expert
Is English your first language?			
Yes	9	6	6
No	4	5	2
Gender			
Female	8	9	6
Male	5	2	2
Highest degree			
BA or BS	8	3	0
MA or MS	4	7	4
PhD	1	1	4
Age (years)			
Mean	31.2	35.8	47.4
Median	29	35	50
SD	6.85	6.1	9.05

Procedures and Data Collection

As novices completed the demographic survey, they were assigned alternately to the control or treatment group. All participants, experts and novices, received an electronic copy of the same case narrative and basic directions for completing their analyses. The case study, based on a real situation encountered by the case authors, was 13 pages long (double-spaced) and dealt with training issues in a manufacturing setting (Simons & Salter, 2007). Participants were asked to describe their understanding of the problem presented in the case narrative. The instructions also stated that participants should spend about 2 hours on their problem analysis and write a case response of about 500 words. In addition, scaffolding guidelines were provided to the treatment group in the form of suggestions, based on the four components of problem representation outlined by Ertmer and Stepich (2005). More specifically, the guidance encouraged novices to synthesize rather than summarize information, focus on principles rather than on surface features, identify relationships among identified issues, and make assumptions (i.e., to be reflective) based on what was stated in the case (see Exhibit 1). After completing their case analyses, participants sent electronic copies of their analyses to the first author.

A comparison group of experts was also included to enable us to examine the differences between the analyses of the experts and the two novice groups. In addition, the responses from this group enabled us to verify that our conception of experts' problem-solving approaches was valid.

TABLE 2
Participants' Self-Reported Instructional Design Knowledge and Experience

	Treatment	Control	Expert
Number of ID courses taken in addition to the introductory course			
Mean	.77	1.18	
Median	1	0	
SD	.83	1.66	
Years of ID experience			
Mean	0.46	0.45	14.13
Median	0	0	12
SD	0.78	.69	6.53
Experience using case studies in instruction (1 = *no experience*; 5 = *a lot of experience*)			
Mean	2.23	2.0	
Median	2.0	2.0	
SD	1.09	.77	
Current level of ID skills (from 1 = *novice to* 4 = *expert*)			
Novice (1)	7	4	
Intermediate (2)	3	5	
Advanced (3)	3	2	
Expert (4)	0	0	
Mean	1.69	1.82	
Confidence for solving ID problems (1 = *not confident*; 5 = *very confident*)			
Mean	2.92	2.91	
Median	3	3	
SD	1.12	.70	

Data Analysis

A rubric was created to evaluate the case analysis reports (see Exhibit 2). The rubric contained four criteria that represented the four dimensions of problem solving (Ertmer & Stepich, 2005). For each dimension, four levels of achievement were identified from expert to novice using a scale from 0 to 3: 0 = *mostly novice*; 1 = *mix, with more novice characteristics*; 2 = *mix, with more expert characteristics*; 3 = *mostly expert*. Content validity was established, prior to using the instrument, by soliciting and incorporating feedback from four scholars who had established reputations in the ID field and had conducted research related to problem solving in the ID domain.

Two members of the research team (the first author and a trained doctoral student) independently scored each case analysis. Both researchers

EXHIBIT 1
Treatment Guidelines for Completing the Case Analysis

Write up your understanding of the case as an individual. Please do not consult with other people regarding the case, but you can use other written resources, if you wish. Your analysis should take no more than 2 hours. To guide you in this task, consider the following suggestions:

- √ Use your own words.
- √ Focus on the "big picture" rather than surface details.
- √ Make assumptions about missing information.
- √ Focus on root causes rather than quick fixes.
- √ Consider the core issues—those that are most central to your understanding of this situation.
- √ Consider the critical issues —those that are likely to have the greatest impact on a successful resolution.
- √ If you identify multiple issues, think about how those issues fit together.
- √ Think about where the issues you identify fit within a traditional instructional design model.

had used the rubric previously to assess the quality of case responses. The researchers began by blind-scoring a small subset of the analysis reports, independent of each other, and then comparing their scores to negotiate an agreed-on score in the case of scoring differences. Following this, each researcher independently analyzed the remaining case responses. The interrater reliabilities (Pearson *r*) for each of the four dependent variables (each dimension of problem representation) ranged from .75 (underlying principles) to .56 (relationships among issues). The interrater reliability scores on the other two dimensions were .74 (coherent representation) and .66 (reflective thinking). A final meeting was held to reach consensus on differing scores. The researchers believed that a consensus score, as opposed to an average score, provided the best representation of the participants' performance levels, as averaging (especially across a scale with a small number of possible scores) would eliminate fine differences, resulting in everyone achieving nearly similar scores.

After coming to consensus on scores for all case responses, average scores for each group (expert, novice treatment, novice control) were calculated on the four dimensions of problem representation. A total score was included as a holistic depiction of the problem representation process. Due to the ordinal nature of the scale used in the scoring rubric, a one-tailed nonparametric statistic (Wilcoxon 2-sample tests) was used. A one-tailed test was used based on the reasonable expectation that the expert group would perform better than either group of novices. Additional comparisons were made in terms of demographics (e.g., years of experience) and the amount of the time spent analyzing the case.

EXHIBIT 2
Scoring Rubric

Dimension	Mostly Novice	Somewhat Novice	Somewhat Expert	Mostly Expert
Score	**0**	**1**	**2**	**3**
Coherent representation	Surface reporting	Has more checks in the novice box	Has more checks in the expert box	Coherent reframing
	• Uses words and labels from case			• Uses own words
				• Uses labels not in the case
	• Labels relate to people or surface details			• Labels are related to key concepts
				• Sees multiple sides to the issue
	• Sees only one side of the issue (blames people)			
Principles versus features	Focus on concrete details	Has more checks in the novice box	Has more checks in the expert box	Focus on abstract principles
	• Takes information at face value			• Interprets the given information
	• Describes issues in terms of what people did wrong			• Looks at underlying principles
				• Considers the design issue involved
	• Does not identify any ID issues			
Relationships among issues	Isolated list of issues	Has more checks in the novice box	Has more checks in the expert box	Coherent list of issues
	• Presents a laundry list of issues			• Organizes issues in an explicit way
	• No apparent discussion of how issues are related			• Makes explicit interconnections among issues
Reflective thinking	Information is an end in itself	Has more checks in the novice box	Has more checks in the expert box	Information is a means to an end
	• Focus on what they don't know			• Makes inferences based on what is known (if-then)
	• Tries to fill gaps in an ID model			• Focused search for information based on conceptualization of issues
	• Mechanical search for information			

Validity and Reliability

True experimental design eliminates most threats to internal and external validity (Gay & Arasian, 2000). While this study did not use random sampling, novice participants were randomly assigned into groups. Therefore, most threats to internal and external validity were controlled for by the design of the study. In addition, various methods were used to establish validity and reliability for the instruments used in this study. The use of electronic documents ensured uniform instructions for all participants and uniform administration of the treatment. The two faculty members on the research team contributed to content and construct validity based on their expertise in differences between ID novices and experts. Scoring bias on the part of the researchers was addressed through the use of a rubric and the process of independent scoring in which researchers scored participants' analysis reports independent of each other. Blind scoring was another method used to reduce scoring bias as researchers did not know whether they scored the response of a novice from the treatment group, a novice from the control group, or an expert. The collection of verbatim data in the form of the analysis report ensured that all researchers had the same data for judging a participant's problem analysis. Validity and reliability in the development and use of the rubric were addressed in the previous section.

Results and Discussion

Experts in this study averaged 14 years of professional ID experience (ranging from 8 to 25 years), while novices averaged less than a year ($M = .46$). Two experts had previous ID experiences in a manufacturing setting (the context of the case problem), and seven of the eight reported having ID experience in a corporate setting. On a scale from 1 to 4 (novice to expert), novices in the treatment and control groups rated their perceived levels of ID competency at an intermediate level ($M = 1.69$ and 1.82, respectively) and their confidence for solving ID problems at an average level ($M = 2.92$ and 2.91, respectively, on a 5-point scale). There were no significant demographic differences between novices in the two groups on any variable assessed (e.g., age, gender, English as a first language, years of previous experience, confidence for problem solving; see Tables 1 and 2). Furthermore, there were no significant differences among the groups in the amount of time spent analyzing the case (control average = 92 minutes; treatment average = 100 minutes; expert average = 114 minutes; $F = 2.19$; $p > .05$).

Table 3 presents the average scores earned by the three groups of participants on the four dimensions of problem representation. Novices in the control group had the lowest average score on each of the four dimensions, and experts had the highest (see Figure 1). Due to the small sample size and the ordinal nature of the scoring rubric, a one-tailed nonparametric statistic (Wilcoxon 2-sample tests) was used (see Table 4). Results indicated a significant difference between experts and control novices on the total

TABLE 3
Means and *SD*s of Four Dimensions of Problem Representation

Dimension or Group	Coherent Representation	Underlying Principles	Relationships Among Issues	Reflective Thinking	Total Score
Expert ($n = 8$)	$M = 2.13$	$M = 2.38$	$M = 2.25$	$M = 1.75$	$M = 8.5$
	$SD = .64$	$SD = .74$	$SD = .89$	$SD = 1.17$	$SD = 2.98$
Treatment ($n = 13$)	$M = 2.0$	$M = 1.69$	$M = 2.15$	$M = 1.54$	$M = 7.39$
	$SD = .91$	$SD = .95$	$SD = .90$	$SD = 1.2$	$SD = 3.64$
Control ($n = 11$)	$M = 1.27$	$M = 1.18$	$M = 1.46$	$M = 1.09$	$M = 5.0$
	$SD = 1.01$	$SD = 1.08$	$SD = 1.04$	$SD = 1.14$	$SD = 3.58$

Note. Scale ranges from 0 (*mostly novice*) to 3 (*mostly expert*).

score ($p = .02$) and on the "coherent representation" ($p = .02$) and "underlying principles" ($p = .02$) dimensions. There were no significant differences between the experts and the treatment novices on any dimension or the total score ($p > .05$). Treatment and control novices showed a significant difference on the "coherent representation" dimension ($p = .04$).

These results support our hypothesis that the use of analysis guidelines can assist novices during the problem-finding process, enabling them to perform more like experts during problem analysis.

These results support our hypothesis that the use of analysis guidelines can assist novices during the problem-finding process, enabling them to perform more like experts during problem analysis. While it is possible that novices are more adept at some aspects of the problem-finding process than others (e.g., describing the relationships among issues), even without support, it is also possible that the guidelines offered more support on some aspects than others (e.g., presenting a coherent representation of the problem). For example, treatment novices were explicitly advised, "Focus on the big picture rather than surface details." This may have encouraged them to specifically consider the key issues in the case narrative, whereas control novices were less likely to do so.

In examining the case analyses, it is clear that at least some participants made intentional use of the guidelines provided. For example, one treatment participant referred specifically to the "core issues" three times in her analysis (suggestion 5 in the guidelines; see Exhibit 1) and described the "critical issue" in her summary paragraph. None of the participants in the control group used these terms. However, it is interesting to note that at least a few participants in each of the three groups scored at the expert level (score = 3) on at least one dimension and that at least one participant from each group scored at the novice level (score = 0) on one dimension. This may simply point to the influence of individual differences on the case analysis process. In addition, it is unclear how many of the participants in the treatment group

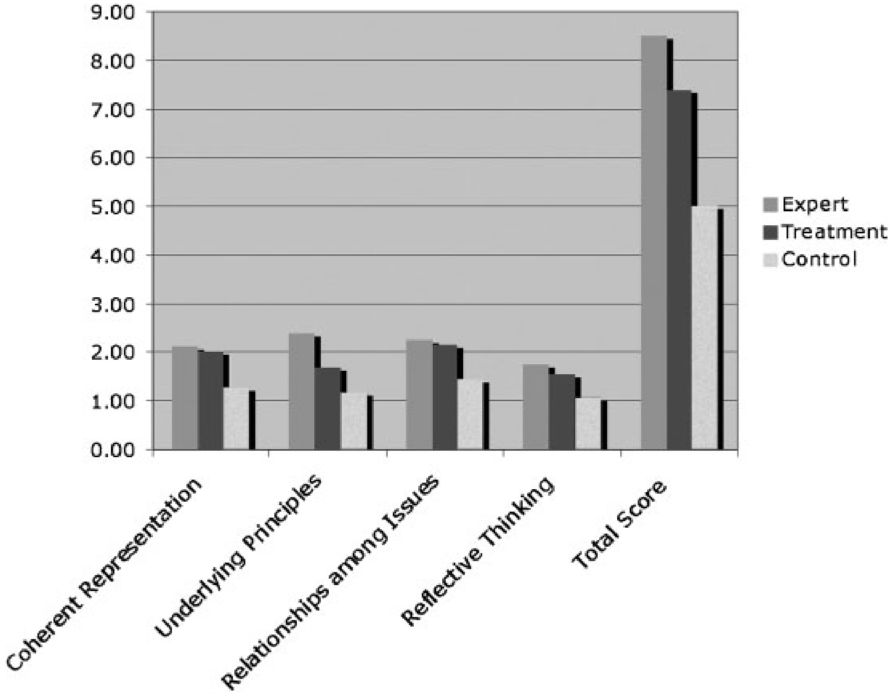

FIGURE 1. Average Scores of the Three Groups on Four Dimensions of Problem Representation.

actually used the guidelines, and to what extent, during their individual problem analysis. Furthermore, we cannot discount the possibility that the small sample size limited our ability to detect real differences among the groups. Future plans include enlarging our sample size to increase our statistical power and implementing strategies to ensure that participants attend to the guidelines provided.

Finally, average scores on each dimension, even for the experts, were not as high as might be expected. There are several possible reasons for this result. First, it may be that the 4-point rubric used to score participants' responses was not sufficiently robust to capture expertise. Second, the experimental task may have unduly constrained the experts' responses. The limitations of a 500-word written response might not have allowed the experts to show the kind of sophisticated problem analyses that would distinguish them from the novices. Finally, it is also possible that the "experts" chosen for the study were not truly experts. Development of expertise in any field is a gradual process, requiring as many as 10 years (Ericsson, 1996) of experience. Furthermore, some authors have argued that experience alone is not enough. For example, Bereiter and Scardamalia (1993) described "experienced nonexperts" as individuals who carry out practiced routines but cannot adapt those procedures to solve unique problems. They suggested that true experts are constantly developing their expertise by "working at the edge of competence" through a process of "deliberate practice" (Horn & Masunaga, 2006). Thus, one possible explanation for the relatively weak performance of the experts in this study is that

TABLE 4
Resulting *p*-Values From Wilcoxon Two-Sample Tests

Dimension and Comparison	Coherent Representation	Underlying Principles	Relationships Among Issues	Reflective Thinking	Total Score
Expert versus control	.02[a]	.02[a]	.08	.12	.02[a]
Expert versus treatment	.47	.08	.49	.37	.22
Treatment versus control	.04[a]	.10	.07	.18	.07

[a]Significant at the .05 level; confidence levels = 95%.

these individuals were actually "experienced nonexperts," as described by Bereiter and Scardamalia (1993). This might be examined in future research by gathering information not only about the amount of their experience but about the nature of those experiences as well.

Implications and Conclusions

It is well documented that ID novices and experts differ in their abilities to arrive at plausible solutions to ill-defined problems, the speed and efficiency at which they do so, and the depth to which and manner in which they attack the problem (LeMaistre, 1998; Rowland, 1992). However, through the use of scaffolds, or guidance, an inexperienced problem solver may be able to leverage a more experienced approach to analyze and solve an ID problem (Ge & Land, 2004).

Results of this exploratory study support previous findings (Dufresne et al., 1992; Ge et al., 2005) suggesting that explicit guidance can increase the problem-solving skills of novices, enabling them to perform more like experts. In this study, guidance was provided in the form of suggestions that were designed to focus novices' thinking when analyzing a problem situation. Based on our analyses, treatment novices performed at a level that was comparable to that of the experts in this study on all four dimensions of problem representation. While a significant difference was not noted between experts and control novices on every dimension of the problem-finding process or between treatment and control novices on three of the four dimensions, a larger sample size may increase the observed differences.

In this study, average scores on the four dimensions of problem representation, as well as the total score, were highest among the experts and lowest among the control novices. While not conclusive, this suggests that the conceptualization of ID expertise, as proposed by Ertmer and Stepich (2005), is useful in distinguishing between the problem-solving approaches of experts and novices. Interestingly, only one dimension, coherent representation, showed significant differences between experts and control novices, as well as between treatment and control novices. Given the suggestion in the literature (Benner, 1984; Larkin, 1979; LeMaistre, 1998; Perez & Emery, 1995) that this is key to experts' problem solving, perhaps this difference should be weighted more heavily, especially if it could be demonstrated that it captures the most important difference between experts and novices. Still, we cannot discount the possibility that the difference observed in this study was due simply to the ease with which this dimension was recognized and scored across the different levels of performance or that the suggestions given to treatment subjects included multiple prompts to support performance on this dimension. Future research is needed that enables us to explain the differences observed in this study. For example, interviews with participants may provide insight into how they interpreted and used the guidelines provided.

Clearly, the acquisition of expert-like schemata takes time (Bransford et al., 2000), yet the use of guidance may reduce the cognitive load inherent in the problem-solving task (Kirschner et al., 2006), enabling novices to acquire these schemata more effectively and efficiently. While the treatment novices in this study did not appear to benefit equally from each of the analysis guidelines provided, there may have been other factors at play. Besides the manner and extent to which the guidelines were used, differences in the types of previous course work and previous experiences (knowledge of the problem domain) may have affected students' analyses. This conjecture is supported by results reported by Ge et al. (2005), who noted that the effectiveness of guidance, in the form of question prompts, depended on several factors. The authors concluded that guidance worked best "when students had sufficient schemata about the content domain, when they were free of pre-assumptions, when they had lower competence level in problem solving, and when they [the question prompts] were used to facilitate cognition and meta-cognition instead of production, such as writing a solution report" (p. 235). Additional research is needed to clarify the extent to which these factors may bear on the effectiveness of the type of guidance used in this study.

Through the use of scaffolds, or guidance, an inexperienced problem solver may be able to leverage a more experienced approach to analyze and solve an ID problem.

It is difficult to both capture and measure expert thinking, and even more difficult to change the way ID novices approach the problem-solving process. While the preliminary results of this study must be interpreted cautiously, they suggest that the use of explicit guidelines based on expert thinking might help novice instructional designers focus on the more critical aspects of a problem situation. Instructional design educators might consider providing these types of suggestions to their students who are just beginning to confront and analyze authentic problem situations. While additional evidence is needed to show the lasting benefit of such guidance, the potential for improved performance appears promising.

References

Benner, P. (1984). *From novice to expert: Excellence and power in clinical nursing practice*. Menlo Park, CA: Addison-Wesley.

Bereiter, C., & Scardamalia, M. (1993). *Surpassing ourselves: An inquiry into the nature and implications of expertise*. Chicago: Open Court.

Bransford, J. D., Brown, A. L., & Cocking, R. R. (2000). *How people learn: Brain, mind, experience, and school*. Washington, DC: National Academy Press.

Dijkstra, S. (2005). Cognition and instructional design for problem-based learning. In J. M. Spector, C. Ohrazda, A. V. Schaack, & D. A. Wiley (Eds.), *Innovations in instructional technology* (pp. 187–206). Mahwah, NJ: Erlbaum.

Dufresne, R. T., Gerace, W. J., Hardiman, P. T., & Mestre, J. P. (1992). Constraining novices to perform expert-like problem analyses: Effects on schema acquisition. *Journal of the Learning Sciences*, *2*, 307–331.

Ericsson, K. A. (1996). The acquisition of expert performance: An introduction to some of the issues. In K. A. Ericsson (Ed.), *The road to excellence: The acquisition of expert performance in the arts and sciences, sports, and games* (pp. 1–50). Mahwah, NJ: Erlbaum.

Ertmer, P. A., & Stepich, D. A. (2005). Instructional design expertise: How will we know it when we see it? *Educational Technology*, *45*(6), 38–43.

Ertmer, P. A., Stepich, D. A., York, C. S., Stickman, A., Wu, L., Zurek, S., et al. (2008). How instructional design experts use knowledge and experience to solve ill-structured problems. *Performance Improvement Quarterly*, *21*(1), 17–42.

Eseryel, D. (2006). *Expert conceptualizations of the domain of instructional design: An investigative study on the deep assessment methodology for complex problem-solving outcomes*. Unpublished doctoral dissertation, Syracuse University.

Gay, L. R., & Airasian, P. (2000). *Educational research: Competencies for analysis and experience* (6th ed.). Upper Saddle River, NJ: Prentice-Hall.

Ge, X., Chen, C., & Davis, K. A. (2005). Scaffolding novice instructional designers' problem-solving processes using question prompts in a Web-based learning environment. *Journal of Educational Computing Research*, *33*, 219–248.

Ge, X., & Land S. M. (2004). A conceptual framework for scaffolding ill-structured problem solving processes using question prompts and peer interactions. *Educational Technology Research and Development*, *52*(2), 5–22.

Gobet, F., & Charness, N. (2006). Expertise in chess. In K. A. Ericsson, N. Charness, P. J. Feltovich, & R. R. Hoffman (Eds.). *The Cambridge handbook of expertise and expert performance* (pp. 523–538). Cambridge: Cambridge University Press.

Horn, J., & Masunaga, H. (2006). A merging theory of expertise and intelligence. In K. A. Ericsson, N. Charness, P. J. Feltovich, & R. R. Hoffman (Eds.). *The Cambridge handbook of expertise and expert performance* (pp. 587–611). Cambridge: Cambridge University Press.

Jonassen, D. H., & Hernandez-Serrano, J. (2002). Case-based reasoning and instructional design: Using stories to support problem solving. *Educational Technology Research and Development*, *50*(2), 65–77.

King, A. (1991). Effects of training in strategic questioning on children's problem solving performance. *Journal of Educational Psychology*, *83*, 307–317.

Kirschner, P. A., Sweller, J., & Clark, R. (2006). Why minimal guidance during instruction does not work: An analysis of the failure of constructivist, discovery, problem-based, experiential, and inquiry-based learning. *Educational Psychologist*, *41*(2), 75–86.

Korth, S. J. (1997). Planning HRD interventions: What, why, and how. *Performance Improvement Quarterly*, *10*(4), 51–71.

Larkin, J. H. (1979). Information processing models and science instruction. In J. Lochhead & J. Clement (Eds.), *Cognitive process instruction*. Philadelphia: Franklin Institute.

LeMaistre, C. (1998). What is an expert instructional designer? Evidence of expert performance during formative evaluation. *Educational Technology Research and Development*, *46*(3), 21–36.

Perez, R. S., & Emery, C. D. (1995). Designer thinking: How novices and experts think about instructional design. *Performance Improvement Quarterly*, *8*(3), 80–95.
Richey, R., Fields, D. C., & Foxon, M. (2001). *Instructional design competencies: The standards*. Syracuse, NY: ERIC Clearinghouse on Information & Technology.
Rowland, G. (1992). What do instructional designers actually do? An initial investigation of expert practice. *Performance Improvement Quarterly*, *5*(2), 65–86.
Scardamalia, M., Bereiter, C., & Steinbach, R. (1984). Teachability of reflective processes in written composition. *Cognitive Science*, *8*, 173–190.
Schoenfeld, A. H. (1985). *Mathematical problem-solving*. Orlando, FL: Academic Press.
Simons, K. D., & Salter, S. M. (2007). Natalie Morales: Managing training in a manufacturing setting. In P. A. Ertmer & J. Quinn (Eds.), *The ID casebook: Case studies in instructional design* (3rd ed., pp. 215–221). Upper Saddle River, NJ: Pearson.
Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, *12*, 257–285.
Taconis, R., Ferguson-Hessler, M. G. M., & Broekkamp, H. (2001). Teaching science problem solving: An overview of experimental work. *Journal of Research in Science Teaching*, *4*, 442–468.

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