Chapter 2
Empirical Evidence on Dynamic Decision-Making and ILEs

Get your facts first, and then you can distort as much as you please.

—M. Twain

2.1 Introduction

Simulation-based decisional aids play a critical role in the education and training of managerial decision-making. In the previous chapter, we have established an empirical research-based assertion that there is an increasing need to design human-facilitated ILEs for improving managerial decision-making in dynamic tasks. This chapter is devoted to the research related to the two core threads of thinking that identify the critical factors for the design of such an interactive learning environment. The core threads are (1) dynamic decision-making (DDM) and (2) simulation-based interactive learning environments. The literature from both the academic and the applied research sources are reviewed. Four critical factors in the design of human-facilitated ILEs are identified: learner factors, dynamic task factors, dynamic decision-environment factors, and facilitator support (i.e., human facilitation) factors. To aid the design of effective decisional aids, a parallel conceptualization of human facilitation is then investigated in the literature on cognitive apprenticeship. Specifically, the analysis of how facilitator support treated in the literature motivates the thinking about the role of training with human-facilitated ILEs.

This chapter is organized as follows: some background concepts are introduced first. Next, we describe the evaluative criteria of DDM, task performance, and learning—*how do we measure performance in dynamic tasks*? After elucidating the dependent variables, this chapter subsequently examines the predictor variables—*what are the leading factors responsible for performance in dynamic tasks*? Specifically, studies on the influence of learner factors, evidence on dynamic task factors, studies in decision-making environment factors, and the role of human

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facilitation are critical. This[1] chapter concludes with (1) a presentation of the process model on the design of effective human-facilitated ILEs to support decision-making and learning in dynamics tasks and (2) an alternative description from cognitive apprenticeship on how to design human facilitation in such ILEs.

2.2 Important Background Concepts

The objective of this book, "to enhance systematically our understanding of and gain insights into the general process by which human-facilitated ILEs are effectively designed and used in improving users' decision-making in dynamic tasks," sets the stage for a critical review of existing research on DDM and learning in ILEs. Before we begin the systematic reflections on the relevant empirical studies, it appears useful to define and describe the two key underlying concepts, (1) DDM and (2) interactive learning environment, here.

2.2.1 Dynamic Decision-Making

DDM situations differ from those traditionally studied in static decision theory in the following ways [16, 35, 38, 84, 93, 94]:

1. *A number of decisions are required rather than a single decision*. To achieve the task objective, the decision-maker, as an individual or in a group, has to make a series of decisions.
2. *Decisions are interdependent rather than independent*. In DDM, current decisions are often constrained by earlier decisions (e.g., certain resources are already committed to prior decisions).
3. *The environment changes*. DDM environment changes either under the influence of the decision-maker's actions and/or due to some externalities.
4. *Closed-loop rather than open-loop causality exists*. In dynamic tasks, multiple, interactive decisions are made over several periods whereby these decisions change the environment, giving rise to new information and thus leading to new decisions.
5. *Structure of a dynamic task is complex rather than simple*. Research in system dynamics (SD) has further characterized such decision tasks by multiple time delays (e.g., it takes time to order and receive a product), nonlinearities[2] (e.g., human productivity can only increase so much and for so long) and uncertainty (e.g., in fuel prices) in and between various variables of the task system.

[1] A much earlier version of this material is published in the Journal of Decision Systems [86].

[2] System dynamics provide powerful and flexible tool (i.e., a table function) to represent these non-linear relationship. Sterman [93] provides excellent illustration of this powerful feature of system dynamics models.

2.2.2 Interactive Learning Environment

As defined earlier in the introductory chapter of this book, an ILE refers to a computer simulation-based interactive learning environment with at least four constituting aspects of it [84, 92]:

1. *Learning and decision-making* about dynamic tasks is the fundamental objective of any ILE.
2. A *computer-simulation model* that adequately represents the reality of the dynamic task is there. Thus, board games are not included in this conception of an ILE.
3. *Human intervention* to aid learning is essential. It means that in any ILE-based learning and training session, facilitator support, and/or peer support is made available as a core requirement.
4. *Active decision-making* occurs. Instead of automatic or programmed-only decisions, decision-makers or learners make decisions for the period of the underlying simulated task of an ILE.

Thus, the majority of computer games including fancy video games that are played for just fun and have no explicit and formal "learning objectives" for the users, won't qualify as ILEs. Therefore, throughout this book, both the terms, "DDM" and "ILE" will be used in the sense described here. Next, we present the review of relevant research.

2.3 A Framework for Experimental Review

One way of organizing an examination of the research is around key variables, which appear in the literature. Task performance, task knowledge including both the structural knowledge and the heuristics knowledge, and transfer learning appear to be the major dependent variables [26–28, 45, 64, 96]. For independent (predictor) variables, four major categories are identified as learner factors: dynamic task factors, decision-making environment factors, and facilitator support factors. These four categories comprise the fundamental aspects of an effective ILE to support decision-making and learning in complex, dynamic environments. A brief description of these dependent variables and categories of independent variables follows.

2.3.1 Task Performance

Researchers have operationalized the construct "task performance" in many ways. Maximizing, minimizing, predicting, achieving, controlling, and performing with task goals are the common measures for task performance. Examples of these task performance measures are provided in Tables 2.2, 2.3, 2.4, and Sect. 2.6 of this chapter.

Table 2.1 Key Predictor Variables

Independent variables' categories	
(a) Learner factors	Whether and how inter-individual differences in task experience, motivation, cognitive styles, etc., impact performance in dynamic tasks
(b) Decision task factors	Whether and how the nature of the task (e.g., contextual and structural variables) impacts performance in dynamic tasks
(c) DDM environment factors	Whether and how the architecture of the decision-making environment, nature of feedback, etc., impacts performance in dynamic tasks
(d) Facilitator support factors	What kind and what level of facilitator support improves performance in dynamic tasks

2.3.2 Task Knowledge

The task knowledge category concerns how well learners in an ILE acquire the knowledge about the task system. To evaluate the learned knowledge, a pre-task and/or post- task questionnaire is often used.

Declarative—Heuristics knowledge distinction is the most commonly employed typology in the surveyed studies. Declarative knowledge pertains to the knowledge of principles, concepts, and facts about the underlying model of the decision task—designer's logic or structural knowledge. It seems common, in the reviewed studies, to measure structural knowledge through written or verbal questions about the precise notion of relationships among various system components or the nature of decision-induced causal variations in the output variables [24, 56, 75]. The other type, procedural knowledge, as against declarative knowledge, concerns how decision-makers actually control or manage the task—operator's logic or heuristics knowledge. In heuristics knowledge questionnaires, the learners are often asked to assess and identify causal relationships between the variables of the task system. Throughout this book, task knowledge is defined as the sum of structural and heuristics knowledge.

2.3.3 Transfer Learning

Transfer learning is used to assess how well decision-makers learn from the previous task by making them attempt another task either in the same domain [57] or in a different domain [3, 50]. In fact, the ultimate aim of any learning and training program in the domain of DDM is to help learners achieve these "transferable skills" [4, 41, 76, 84].

2.3.4 Independent Variables' Categories

Table 2.1 provides a brief description of these categories.

After highlighting the overall characteristics of the existing empirical research, the review of the empirical research will proceed as follows: first, the question of whether and how the learner characteristics impact task performance and learning will be considered. Second, the research that addresses the effects of the nature of the decision task will be considered, followed by a discussion about the influences of the decision-making environment. Finally, impact of facilitator support on subjects' task performance and learning will be examined.

2.4 Characteristics of the Existing Research on DDM and Learning in ILEs

There are numerous studies on dynamic decision-making and learning with ILEs which use decision task factors as an integral part of larger manipulations. There are relatively few studies, however, where the nature of facilitator support manipulation is such that the effects of the form of support and the level of support can be determined clearly. A moderate number of studies examine empirically the influences of learner characteristics and features of the decision-making environment on task performance and learning [86].

Over 40 experimental studies provide clear information about the nature of predictor manipulations to be considered here. In most of the studies, task performance was the major dependent variable, while in a few cases "task knowledge" and "transfer learning" were the outcome variables of the studies. These 40 empirical studies are listed in Tables 2.2, 2.3, 2.4, and 2.5 of this chapter. For each study, the used ILE, dynamic task structure, and a short summary of major results are provided in each of these tables.

2.5 On the Influence of Learner Factors

Figure 2.1 depicts the key variables determining the effects of individual differences on task performance and learning in dynamic tasks. Table 2.2 lists several empirical studies which report the impacts of learner factors on DDM.

Among the independent variables, 'task experience' explores the relationships of decision inputs and outputs by trial and error. It enhances causal understanding of task structure, establishes reliable decision rules, and as a result, improves task performance [55]. For example, task experience may affect the subject's behavior of information use [18] and have a positive effect on task performance [2, 9]. On the other hand, Broadbent and Aston [22] established that subjects could learn through task practice to make better decisions than they had when the task was new to them. Yet, the same subjects could not improve their ability to answer verbal questions. Conversely, verbal instructions can improve subjects' question answering ability but not their control performance [9]. This surprising finding has been replicated in different experimental settings and task environments [10, 21, 99].

These results point to two important implications for DDM research and practice: (1) expertise development in dynamic tasks through task experience

Table 2.2 Impact of learner factors on DDM

References	ILE (s)	Task structures	Major findings
Bakken [2]	SD-based simulation	Delays, nonlinearity and feedback loops	Positive effect of TE on TP; positive effect of prior business experience on SK
Bakken et al. [3]	PEOPLE EXPRESS	Delays, nonlinearity and feedback loops	Subjects with no PPE transferred insights markedly better than those with PPE
Berry and Broadbent [7]	Sugar production game	Delays	Positive effect of TK on TP; TE is positively related to SK and negatively related to HK; positive effect of TE on TP
Brehmer and Svenmark [19]	Sugar production game	Delays	TE decreased the decision time in terms of average trial time
Diehl and Sterman [31]	Stock management task simulation	Delays, nonlinearity, and feedback loops	Positive effect of TE on TP
Grubler et al. [49]	JEANSFABRIK- a business management simulated system	Delays, nonlinearity and feedback loops	Absolute frequency of planning periods was not but amount of variation of input variables was significantly related to TP; subjects with systematic-elaboration strategy were more effective than those with global exploration strategy in TP
Hayes and Broadbent [50]	Computer person game	Delays	TE through selective model is positively related to SK and unselective mode of learning induces procedural HK
Jansson [58]	MORO	Delay, nonlinearity, and feedback loops	Systematic elaboration of instruction and goal planning instruction, both improved TP and HK than those in control group
Jansson [58]	MORO	Delay, nonlinearity, and feedback loops	Significant differences between the experimental groups only on the single feed forward part of questionnaire (HK)
Jansson [58]	MORO	Delay, nonlinearity, and feedback loops	Systematic elaboration of instruction and goal planning instruction, collected more information, applied more information, and showed increased in decision time
Kleinmuntz [60]	Medical decision-making task simulation	Delay, nonlinearity, and feedback loops	Schema-driven acquisition was superior to random acquisition in TP

(continued)

Table 2.2 (continued)

References	ILE (s)	Task structures	Major findings
Maxwell [75]	Social welfare Model-JOBS-based simulation game	Delay, nonlinearity, and feedback loops	No effect of TE on TP No effect of PTK on SK
Njoo and de Jong [80]	A system in control theory simulation	Delay, nonlinearity, and feedback loops	Higher PTK leads to higher SK
Paich and Sterman [81]	Market strategy simulation game	Delay, nonlinearity, and feedback loops	Positive effect of TE on TP
Putz-Osterloh et al. [83]	MORO	Delay, nonlinearity and feedback loops	Generating and testing of hypotheses lead to improved TP
Trees et al. [101]	STRATEGUM-2	Delay, nonlinearity and positive loops	Positive effect of cognitive styles on TP
Qudrat-Ullah [85]	FishBankILE	Delay, nonlinearity. and positive loops	Positive effect of task knowledge on TP; positive effect of task knowledge on TL

TP task performance; *TK* task knowledge; *SK* structural knowledge; *HK* heuristics knowledge; *TL* transfer learning; *PTK* Prior task knowledge; *TP* task performance; *PPE* prior professional experience

Table 2.3 Impact of dynamic task factors on DDM

References	ILE (s)	Task structures	Major findings
Bakken [2]	SD-based simulation	Delays, nonlinearity, and feedback loops	Low frequency of task oscillations leads to better TP
Beckmann and Guthke [5]	A complex, dynamic system simulation	Feedback loops	Subjects in semantics group outperformed those in abstract group in terms of TP
Beckmann and Guthke [5]	A complex, dynamic system simulation	Feedback loops	Subjects in semantics group has no relation but subjects in semantics group has positive relation to SK
Brehmer [17]	FIRE FIGHTING	Delays, nonlinearity, and feedback loops	Detrimental effect of TD on TP
Berry and Broadbent [7]	FIRE FIGHTING	Delays, nonlinearity, and feedback loops	TI improves SK but not about indirect or crossed relationships (HK)
Diehl and Sterman [31]	Stock management task simulation	Delays, nonlinearity, and feedback loops	An increase in TD decreases TP; A stronger FG deteriorate subjects TP
Gonzalez et al. [44]	SITMECOM	Delay, nonlinearity, and feedback loops	Positive effect of TT on TP
Gonzalez et al. [44]	SITMECOM	Delay, nonlinearity, and feedback loops	Positive effect of TT on SK
Gonzalez et al. [46]	LEARN!	Delay, nonlinearity, and feedback loops	TT has a positive influence on TP
Huber [57]	BREEDING LIZARDS TASK	Delay, nonlinearity, and feedback loops	No effect of TSE on TP
Machuca et al. [72]	SITMECOM	Delay, nonlinearity, and feedback loops	TT has positive influence on subjects' acquisition of SK
Mackinnon and Wearing [73]	Social welfare Model-JOBS-based simulation game	Delay, nonlinearity, and feedback loops	Detrimental effect of TNV and RV on TP but positive effect of IBS on TP
Moxnes [78]	Renewable-resource-management flight simulator	Delay, nonlinearity, and feedback loops	Subjects with TT with full TI performed poorly than benchmark with imperfect information

(continued)

Table 2.3 (continued)

References	ILE (s)	Task structures	Major findings
Paich and Sterman [81]	Market strategy simulation game	Delay, nonlinearity, and feedback loops	Subjects perform poorly as complexity (TD and FG) increases
Sterman [94]	BEER GAME	Delay, nonlinearity, and feedback loops	Detrimental effect of TD and positive feedback gain on TP
Sterman [95]	BEER GAME	Delay, nonlinearity, and feedback loops	Detrimental effect of TD and positive feedback gain on TP
Yang [106]	A simulated ecosystem game	Delay and positive loops	Subjects with number goal performed better on TP than those with ratio and subsystem goal
Yang [106]	A simulated ecosystem game	Delay and positive loops	Subjects with number goal performed better on TK than those with ratio and subsystem goal
Young et al. [107]	STRATEGUM-2	Delay, nonlinearity, and feedback loops	Detrimental effect of uncontrollable positive feedback loops on TP
Diehl and Sterman [31]	Stock management task simulation	Delay, nonlinearity, and feedback loops	Effects of TD and FG on decisions are insignificant
Young et al. [107]	STRATEGUM-2	Delay, nonlinearity, and feedback loops	Uncontrollable positive feedback loops has significant influence on decision scope
Wheat [103]	MacroLab	Delay, nonlinearity, and feedback loops	Subjects provided with CLD-based TI performed better on TK
Capelo and Dias [24]	SD-based business simulator	Delay, nonlinearity, and feedback loops	Subjects provided with causal strategy maps improved on TP and TK than those without it
Dhawan et al. [30]	One stock dynamic task	Delay and feedback loop	Subjects performed poorly on TP in a complex task than a simple task

TP task performance; *SK* structural knowledge; *HK* heuristics knowledge; *TL* transfer learning; TD: time delay' *FG* feedback gain; *TI* task information; *TT* task transparency; *TSE* task semantic embedding; *TNV* total number of variables; *RV* random variation; *IBS* interaction between subsystems; *CLD* causal loop diagram

Table 2.4 Impact of decision-making-environment factors on DDM

References	ILE (s)	Task structures	Major findings
Bakken et al. [3]	SD-based simulation	Delays, nonlinearity, and feedback loops	Subjects transferred insights (TL) from the first to second simulator
Benbasat and Dexter [6]	Marketing decision-making simulator	Judgmental task	TP of FD with color-enhanced reports was 73 % better than those without such reports
Benbasat and Dexter [6]	Marketing decision-making simulator	Judgmental task	No TP differences were found
Berry [8]	Sugar production game	Delays, nonlinearity, and feedback loops	Subjects with "observation" condition were not able to show improvement in TP
Berry [8]	Sugar production game	Delays, nonlinearity, and feedback loops	Subjects in "observation" condition did not improved SK
Brehmer and Svenmark [19]	FIRE FIGHTING	Delays, nonlinearity, and feedback loops	Subjects in hierarchical architectural condition performed better on TP than those in networked condition
Brehmer and Svenmark [19]	FIRE FIGHTING	Delay, nonlinearity, and feedback loops	Subjects in both conditions showed no effect on decision time
Breuer and Kummer [20]	A simulation game	Delay, nonlinearity, and feedback loops	Subjects in Process Learning condition exhibited significant improvements in their cognitive strategies (HK)
Blazer et al. [14]	MCPL Task	Prediction task	Subjects who received TI showed significantly better TP than subjects who received no feedback
Hsiao [56]	BEER GAME	Delay, nonlinearity, and feedback loops	Providing benchmark outcome improves subjects TP
Hsiao [56]	BEER GAME	Delay, nonlinearity, and feedback loops	Heuristics knowledge more effectively contributes to task performance than structural knowledge
Hsiao [56]	BEER GAME	Delay, nonlinearity, and feedback loops	Providing benchmark outcome improves subjects SK and HK
Putz-Osterloh et al. [83]	MORO	Delay, nonlinearity, and feedback loops	Graphical feedback alone is ineffective in improving TP

(continued)

Table 2.4 (continued)

References	ILE (s)	Task structures	Major findings
Putz-Osterloh et al. [83]	MORO	Delay, nonlinearity, and feedback loops	Learning by doing alone is ineffective in improving TP
Putz-Osterloh et al. [83]	MORO	Delay, nonlinearity, and feedback loops	Unstable graphs with experience cause an improvement in TP
Putz-Osterloh et al. [83]	MORO	Delay, nonlinearity, and feedback loops	Graphical feedback alone is ineffective in improving TP
Putz-Osterloh et al. [83]	MORO	Delay and positive loops	No difference in SK scores between stable and unstable conditions
Sengupta and Abdel-Hamid [90]	Software project management game	Delay and positive loops	Subjects in CF group had the best TP, followed by FF and OF groups
Sengupta and Abdel-Hamid [90]	Software project management game	Delay, nonlinearity, and feedback loops	More use of CF and not more information per se improved subject's TP
Sengupta and Abdel-Hamid [90]	Software project management game	Delay, nonlinearity, and feedback loops	Better performers were positively associated with higher aggregate use of CF
Sengupta and Abdel-Hamid [90]	Software project management game	Delay, nonlinearity, and feedback loops	Subjects in CF group used longer decision time, followed by FF and OF
Sengupta and Abdel-Hamid [90]	Software project management game	Delay, nonlinearity, and feedback loops	Subjects in OF group fluctuated the most, followed by FF and CF
Howie et al. [54]	STRATEGUM-2	Delay, nonlinearity, and feedback loops	Salient interface design improve TP and TK
Gonzalez [43]	Water purification plant task	Delay, nonlinearity, and feedback loops	Feed forward improved TP; neither CF nor OF improved TP
Kopainsky and Sawicka [62]	Reindeer pasture management task	Delay, nonlinearity, and feedback loops	Use of simulator improved TP and TK

TP task performance; *SK* structural knowledge; *HK* heuristics knowledge; *TL* transfer learning; *OF* outcome feedback; *CF* cognitive feedback; *FF* feed forward

Table 2.5 Impact of Human Facilitation on DDM

References	ILE (s)	Task structures	Major findings
Gröbler et al. [46]	LEARN!	Delay, nonlinearity, and feedback loops	Information on task structures improved casual understanding about the task variables
Khalifa et al. [59]	SD-based simulation task	Delay, nonlinearity and feedback loops	Collaborated learning content facilitation had no impact on learning
			Process facilitation was more influential on learning
Langley and Morecroft [66]	Oil industry simulation task	Delay, nonlinearity, and feedback loops	Structured feedback improved TP and TK
Qudrat-Ullah [84]	FishBankILE	Delay, nonlinearity, and feedback loops	Structured debriefing improved TP, SK, HK, and TL
Lurie and Swaminathan [69]	Inventory management task	Stochastic demand	More frequent feedback declined TP
Borštnar et al. [15]	SD-bases simulation task	Delay, nonlinearity, and feedback loops	Group process facilitation improved on task motivation, HK, and task effort while non-structured process facilitation produced reverse effects
Qudrat-Ullah [85]	FishBankILE	Delay, nonlinearity, and feedback loops	Subjects provided with causal loop diagram-based instructions did better on TP than those without such instructions
Dhawan et al. [30]	One stock dynamic task	Delay and feedback loop	Training with system dynamics-based simulator improved TP and TK

TP task performance; *SK* structural knowledge; *HK* heuristics knowledge

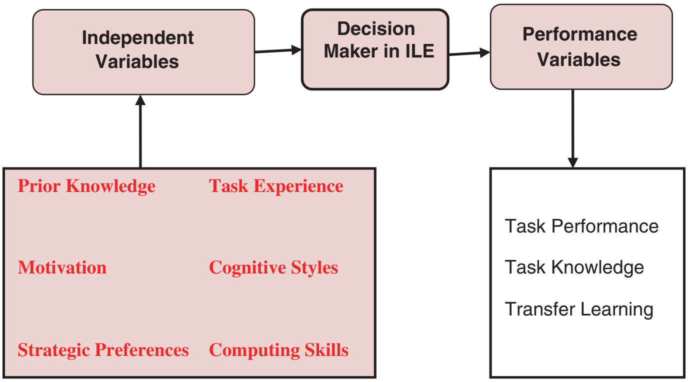

Fig. 2.1 Learner Factors and Performance in Dynamic Tasks

builds via tacit knowledge—knowledge that can't be verbalized and (2) assessment of learning and decision-making skills in dynamic tasks should be measured in multiple dimensions. That means measurement through "task performance" alone won't capture the developed learning and knowledge in dynamic tasks. This is even more important in the assessment of ILE-based training sessions where the decision-makers go through rich learning experiences (e.g., task exploration, hypothesis testing, information searching, and feedback seeking). They may not show improvement in task performance but may well develop say, structural knowledge, about the task system. With more practice and the utilization of the learned task knowledge, one can expect them to perform better on task performance in the future—an improvement in their transfer learning.

Motivation of the learners participating in an ILE session has a positive influence on their simulation game performance [34, 87]. Dörner et al. [34] in their well-known LOHHAUSEN study showed that DDM performance was related to motivational and emotional factors to a greater extent than intellectual factors. However, Beckmann and Guthke [5] suspected that LOHHAUSEN findings might have been due to the fact that the subjects' interactions with the system were mediated by the experimenter. We did not find any subsequent study to empirically resolve this rather inconclusive finding. In the design of an ILE, therefore, the inclusion of motivational artifacts is likely to engage the users in learning and performing better in dynamic tasks.

Computing skills have been demonstrated to be helpful for familiarization with the task systems but not in task performance [101]. The irrelevance of computing skills to task performance seems predictable as the subjects in DDM studies are allowed to spend sufficient time to familiarize themselves with computer simulation interfaces [55]. Therefore, in the design of effective ILEs, especially for the purpose of learning assessment, enough efforts should be directed in ensuring that all the learners are comfortable with actual decision-making and feedback features of the underlying computer simulation-based system.

Cognitive styles, and more recently, personality indicators such as the Myers-Briggs Type Indicator (MBTI), of the learners have been hypothesized to have a significant effect on performance in simulated experiential learning [42]. However, only a few of the evaluated empirical studies have supported the effect of cognitive styles on dynamic decision tasks performance [29, 101]. For instance, Trees et al. [101] investigated the extent to which cognitive styles of the learners helped explain individual differences in dynamic decision-making in a computer simulated game environment. They reported that subjects who scored higher on the 'Abstract' component of the Gregoric test had marginal explanatory power for task performance. Overall, in dynamic tasks, effort directed towards the development of an adequate model of the task system is a better predictor of task performance than the cognitive styles of the decision-makers.

Another learner factor, prior knowledge, refers to the general domain knowledge the learners bring into an ILE session, either from their academic background or via structured training consultations or both. Generally, researchers have shown a reasonable recognition of prior knowledge for decision behavior and task performance. The evaluated studies nevertheless provide inconclusive evidence. Some studies provide support in a fairly general sense to the argument that domain knowledge is an important predictor of control performance, as detailed by Funke [39].

On the other hand, Bakken [2] reported that subjects with business management backgrounds performed better in a real estate game, which presumably required more management expertise, than in an oil tanker game. It means subjects were able to apply the domain-specific learned knowledge. However, Maxwell's study [75], a two-day session on simulation techniques and general task knowledge, showed no effect of training on task performance.

More recently, using FishBankILE, Qudrat-Ullah [85] empirically investigated the impact of task knowledge on subjects' performance in dynamic tasks. This study found that (1) increased task knowledge about the dynamic task does improve subjects' task performance and (2) transfer learning. This, again, points to the need of design and development of alternative decisional aids, capable of supporting the development of "transferable skills" in complex, dynamic tasks.

Decision-makers' strategies and strategic preferences play an important role in their performance in dynamic tasks [58, 79, 84]. Strategic preference refers to the decision-making strategies (e.g., systematic variations of input variables, random exploration, and heuristics-based strategies) subjects use when exposed to dynamic tasks. Using BIOLOGY LAB, Vollmeyer and Holyoak [102] analyzed the strategies subjects use when exposed to various tasks such as exploring, controlling, and predicting. They found that the subjects using systematic variations of a strategy performed better in representation of the system and in prediction of system states than did subjects who employed unsystematic variations of a strategy. Surprisingly however, no group differences were reported for subjects' control performance. In contrast, Putz-Osterloh, Bott, and Koster [83], using the DYNAMIS microworld, found significant improvements in structural knowledge for subjects using efficient strategies for intervention. In fact, ILEs are purported to support experiential learning [89]. Thus, it seems plausible to hypothesize that in ILE sessions, active exploration and testing of various decision rules by learners could accrue significant learning benefits.

Hogarth and Makridakis [52, 53] examined the effects of differential consistency in a dynamic decision-making environment. In the context of a competitive business game ("Markstrat"), subjects were pitted against two kinds of decision rules: one where rule were applied consistently ("arbitrary-consistent"); the other where rules were subject to a random component ("arbitrary-random"). The arbitrary-consistent rules outperformed, on average, 41 % of human opponents; the corresponding figure for arbitrary-random being 19 %.

The results of Jansson' [58] study showed that the control performance of both the groups who received heuristic instructions was significantly better than that of the control group. Jansson, through the post-experimental questionnaire, attributes these differences in performance to the adequate system model the subjects had [25]. These findings are in sharp contrast to a fairly large amount of research that documents people's problems dealing with complex systems [10, 19, 20, 23, 32, 81, 94, 95]. On the other hand, in the real world, we routinely and on a daily basis witness fellow human beings performing successfully in complex systems (e.g., doctors in emergency rooms, pilots in the cockpits, commanders in the military battle fields, scientists in research labs). Therefore, we need to move beyond just reporting people's poor performance in dynamic tasks. Instead, the search and research for support mechanisms that help people develop expertise in dynamic task is overdue.

Overall, among the learner factors that we have reviewed above, prior knowledge and experience that the learners possess and decision strategies they adopt while performing dynamic tasks stand out as critical factors for successful performance in dynamic tasks.

2.6 Evidence on Dynamic Task Factors

Figure 2.2 shows the major decision task factors influencing task performance and learning in ILEs. In particular, DDM researchers have investigated the impact of semantic embedding, task complexity, and task transparency. Table 2.3 lists several empirical studies which report the impacts of various dynamic task factors on subjects' DDM.

Context familiarity is an important prerequisite for better decision-making and learning performance in ILE-based training sessions [84]. Semantic embedding of the task refers to whether or not the task is couched within a well-understood and familiar context. Funke [39] mentions two studies dealing with the impact of semantic embedding. In the first study, Hess [51] compared two different semantic embedding for the same system, EPIDEMIC. The change in semantics from "flu" to "small-pox" epidemic changed subjects' behavior drastically; in the more "dangerous" situation, subjects tended to be much more involved, and to take more time in making their decisions. In the second study, Beckmann and Guthke [5] compared two semantic embedding (CHERRY TREE vs. MACHINE) of the same system structure with respect to subjects' knowledge acquisition strategies. They reported that the semantically rich embedding seemed to prevent the problem solvers from

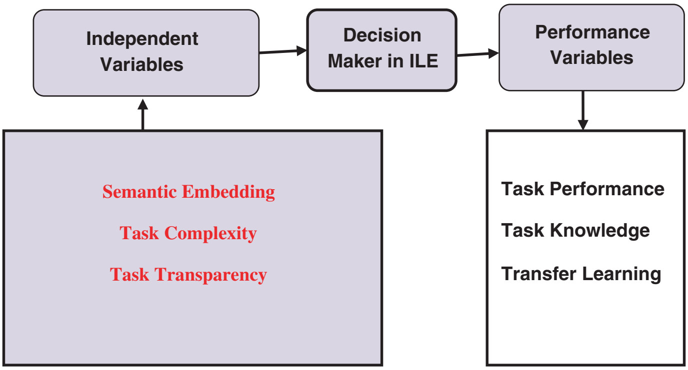

Fig. 2.2 Dynamic Task Factors and Performance in Dynamic Tasks

using efficient analytic knowledge acquisition strategies. In dynamic tasks, any additional cognitive load faced by the decision-makers is likely to impede their learning and performance [28, 84].

Bakken et al. [3] conducted an experiment where two computerized decision-making games were used with two different cover stories. The results showed no difference between subjects who started with either of the semantics and continued with the other. This suggests that the role of semantic embedding in dynamic task performance is limited at best.

Dynamic tasks, by their nature, are complex tasks. In the DDM research community, the concept of task complexity has been operationalized through various indicators. Some common indicators of task complexity include real-time simulation tasks, total number of variables, interaction between subsystems, random variation, miscellaneous task characteristics, positive feedback and gains, lagged effects, decision effectiveness, and frequency of oscillations [18, 31, 56, 78, 81, 94].

Mackinnon and Wearing [73], using a welfare administration model, examined the impact of a total number of variables, interaction between subsystems, and random variation on task performance. The empirical evidence showed that an increase in the total number of variables and random variation built into the task would deteriorate the subjects' task performance. However, contrary to their hypothesis, subjects performed better when interaction between subsystems existed. On the other hand, research on SD (for further details, see in [37, 93]) suggests that negative feedback loops can stabilize systems' behavior through interaction between subsystems. As a result, uncertainty and random variations would never be problematic in dynamic task systems as long as the error caused by decisions can be reduced through the interaction of subsystems where stabilizing negative feedback loops dominate system behaviors. The same reasoning applies to the impact of increasing the number of variables.

The pioneering work of Sterman [94, 95], "the misperception of feedback hypothesis," attributes the decision-makers' failure to manage dynamic decision tasks to their inability to identify endogenous positive feedback loops responsible for enlarging apparently tiny decision errors and side effects. Many researchers [31, 81, 107] have confirmed this hypothesis by varying the strength of loops. It was also shown that the decision time allocated by the subjects to make decisions does not increase in proportion to the increasing strength of positive gains. Young et al. [107], using the micro-world STRATEGEM-2, tested whether the decision scope was reduced when decision-makers triggered some uncontrollable positive feedback loops. They reported strong evidence for the hypothesis.

Sterman [94] reports two facets of subjects' failure to appreciate time delays. First, they ignore the time lag between the initiation of a control action and its full effect. Second, they are overly aggressive in correcting the discrepancies between the desired and actual state of the variable of interest. Logically, the same failure to appreciate the delayed effect of decisions also applies for counter-correction because subjects fail to understand the full effect of their previous discrepancy correction. There has been much confirmatory evidence to the detrimental effect of time delays on task performance, coming from empirical studies adopting various task and experimental settings (e.g., [10, 11, 16–18, 30, 31, 78, 81, 94]). Thus, the degrading effect of lagged effects on task performance bears a high degree of external validity. Therefore, an effective ILE-based training session should allow the users to appreciate and understand the impacts of delays between various variables of the task system.

In general, the surveyed studies [9, 23, 58] rejected the hypothesis that subjects receiving task information can acquire more correct verbal knowledge. However, Berry and Broadbent [7] found that providing subjects with task information improved only the direct relationships and not the indirect relationships. Therefore, in ILE-based training sessions, it seems plausible to assume the positive role of task information on the development of task structural knowledge but not the insight-oriented heuristics knowledge.

Several researchers (e.g., [28, 44, 46, 47, 67, 70, 72]) have explored the issue of task transparency. The key argument developed is that availability of mechanisms that provide task structural information to the learner introduces task transparency and hence improves subjects' task performance. Learners are able to inspect, criticize, or even improve the underlying model. Gröbler et al. [46] performed an experiment to evaluate the relevance and effects of structural transparency. The results showed that a presentation about the structure of the system had a positive influence on subjects' task performance. In contrast to the improved game performance, subjects were not able to transfer their acquired knowledge to solve the post-knowledge test in the experiment.

Task transparency has also been operationalized as the provision of decision heuristics. The effect of decision heuristics on task performance appears to be positive [56, 71]. For example, Yang's [106] empirical study confirms that subjects are able to achieve better control and understanding of tasks by being trained with the explicit goal statement. Consistent attention and focus on achieving the stated goals appear to lessen the distractive cognitive demands. Instead, learners' efforts are well spent on developing the understating of causal relationships between task system variables. Improved understanding of causal relationships leads to better task performance and improved task knowledge [24]. In this book, our conception of an ILE, where human facilitation is the core component, is consistent with these empirical findings.

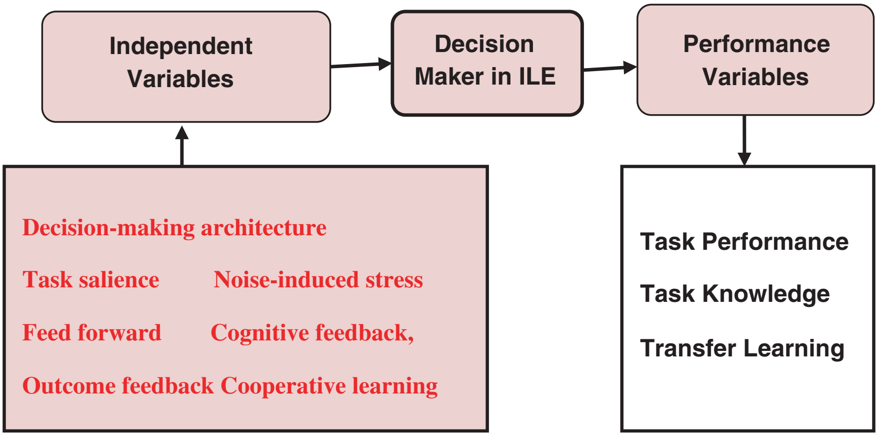

Fig. 2.3 Decision-Making-Environment Factors and Performance

2.7 Studies on Decision-Making Environment Factors

Figure 2.3 shows the major factors of a decision-making environment impacting task performance and learning in dynamic tasks. Table 2.4 lists several empirical studies which report the impacts of various decision-making environment factors on subjects' DDM.

In ILEs, subjects make active decisions over the period of the underlying simulation task. How do active decision-makers versus passive observers perform in a computer simulation-based task environment? In this regard, Funke [39] provides an account of two studies [8, 40,] exploring the impact of the type of tasks on task performance. The results of the first study [40] showed that subjects with active intervention performed well in control performance but poorly on a knowledge verbalization measure. Interestingly, the passive observers, who were poor in control performance, showed improved performance on task system knowledge.

When the relationship between the variables of a task system is direct and shows plausible causal relationships, these relations are termed as "salient relations." In this context, Berry [87] found that through learning by observation, both knowledge acquisition and control performance was possible when the task was changed from a task with nonsalient relations to a task with salient relations among the system variables. Thus, a learning environment that facilitates the development of casual understating about the key variables of the dynamic task [82], is likely to help the learners perform better in complex, dynamic tasks.

When decision-makers are provided the opportunity to practice with SD-based simulator, their task performance and task knowledge improves versus those without such a simulator [62]. This empirical evidence provides further support to our conception of an ILE where SD-based simulation model is one of its core components.

The decision-making architecture is a decisional aid that, among all the predictors, has a unique position in that it points to an important organizational issue—how the communication network embedded in the organizational structure affects task performance [19]. Brehmer and Svenmark [19], distinguished between two types of organizational structure: the networked architecture where each subject can communicate with each other and the hierarchical architecture where all communication has to be channeled through one subject as a commander. The results showed that the subjects performed better in the hierarchical environment than in the networked architecture. No other study has replicated this finding about decision-making environment architecture.

The only study evaluating the effects of noise-induced stress on task performance is by Dörner and Pfeifer [33], cited in Funke's [39] review. They found that although stress did not affect the number of errors made, it did affect which types of errors were made (e.g., the subjects under stress showed a more reactive type of behavior). This finding has an important implication for the design of an effective ILE. In training sessions with ILEs, decision-makers should not be faced with stressful learning situations. Instead, ILEs should provide the learners conducive and pleasant experiences.

Decision-making and learning in dynamic tasks is a feedback process [93]. In DDM literature, three types of information feedback—feedforward, outcome feedback, and cognitive feedback—are identified. Feedforward refers to a set of pre-task heuristics, available to the decision-makers, for effectively performing the task [12, 74], outcome feedback pertains to the provision of past decisions and outcomes to the subjects [94, 95], and cognitive feedback is conceptualized as information reflecting task structure and the decision-making environment [6, 13, 14].

It has been argued that outcome feedback permits the decision-makers to adjust to the general direction of judgment through a judgment-action-feedback loop [52]. Their next decision is based on what earlier decisions have resulted in an opportunity to adjust one's future decisions. However, such a utility of outcome feedback in dynamic tasks, where often a decision and its consequence are separated in both time and space, is limited. Kleinmuntz [60] has argued that availability of Bayesian probability helps subjects with task performance. Sanderson [88], on the other hand, supports that making previous decisions and outcomes available to subjects would prevent them from developing correct task knowledge and degrade their task performance [55]. Other studies show similar dysfunctionalities in performance when subjects are exposed to repeated trials even with minimal delays in feedback [16] and are presented with complete decisions and outcomes [79].

Sengupta and Abdel-Hamid [90], using a software development projects simulator, investigated the differential effects of the three types of information feedback. Their results demonstrate the incremental efficacy of cognitive feedback and feedforward over outcome feedback in improving task performance. The subjects receiving outcome feedback alone showed inferior task performance while addition of cognitive feedback improved their task performance in the complex software project task. Dynamic tasks often present the decision-makers with demanding structural information processing scenarios. Cognitive feedback appears to help the decision-makers perform better in dynamic tasks by means of reducing this information processing workload.

Use of heuristics has shown to improve the performance of decision-makers in dynamic tasks. Hsiao [56] tested the hypothesis that providing a benchmark outcome improves task performance. The empirical evidence supported the hypothesis. Furthermore, he showed that better performance came from improving the anchoring and adjustment of the heuristics the subjects used. The results also revealed the surprising finding that providing the full-featured outcome feedback actually degraded the task performance. Therefore, the provision of outcome feedback alone in an ILE is of limited help, if any. Using, WPP, a simulation-based dynamic task, Gonzalez [43] found a positive effect of feedforward on task performance but neither outcome feedback nor cognitive feedback improved performance.

Employment of cooperative learning methods was suggested as an effective design condition for problem-oriented simulations [20, 77, 98, 100]. In dynamic decision-DDM literature, Funke [39] provides some interesting insights regarding the effect of individual versus group settings on learning in dynamic environments. For instance, in Badke-Schaub's [1] study, groups had problems in defining a common goal but had advantages in searching problem-relevant information. Groups also identified more proposals for solutions but faced difficulty in selecting one or more of these proposals. Building consensus on using a particular decision strategy requires the participants to articulate and justify their preferred decision strategy. ILE sessions, with limited time, hardly could afford such a decision-making process. However, with a smaller group size (i.e., two or three members in a group), consensus-based decision-making process can work. With smaller groups in ILEs, the benefits of peer-learning can facilitate the improved performance in dynamic tasks.

In ILEs, the structure of "interface" between the underlying simulation and the users has significant impact on the performance. Contrary to the misperception of feedback hypothesis [94, 95], dynamic decision-making performance can be improved by making the feedback structures of the environment more salient using human–computer interface design principles [54]. Using STRATEGUM-2 in their experiment, they reported that the new interface of Strategum-2 led to improved task performance and greater improvement in task knowledge about the underlying microworld. Therefore, to effectively support learning and decision-making in dynamic tasks, the design of ILEs should incorporate mechanisms that allow users to better understand the task structures.

2.8 Role of Human Facilitation

Many researchers seem convinced that for effective learning to occur, especially when the task environment is complex and where learning is considered as a progression toward expertise (e.g., as in Sternberg [97]), human facilitator support becomes critical [26, 28, 36, 45, 61, 63, 91, 104, 105]. Figure 2.4 shows the major factors of human facilitation impacting task performance and learning in dynamic tasks. Table 2.5 presents several empirical studies which report the role of human facilitation in subjects' DDM.

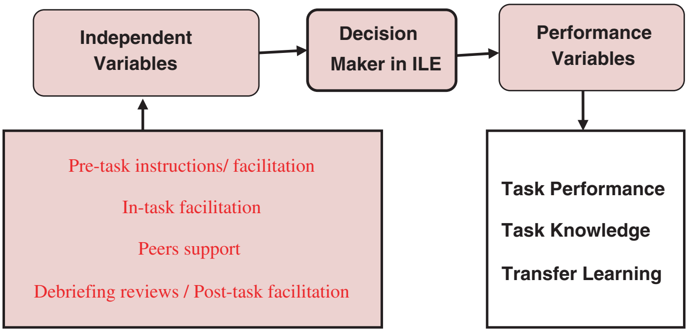

Fig. 2.4 Facilitators Factors and Performance in Dynamic Tasks

In dynamic tasks, where decision-makers are expected to have an adequate understanding of the task system, developing dynamic decision-making skills is more of a process than an outcome. In fact, people become experts through diverse learning experiences across various tasks. We, following Sternberg's view, believe that learning in dynamic tasks is the acquisition of task knowledge and heuristics development on a spectrum—people gain expertise at varying degrees [97]. The role of human facilitation in clarifying the misconceptions about the task systems and helping the decision-maker's develop an adequate model of the task system seems critical.

In education, the role of tutorial support is well recognized. Wood et al. [105] studied tutor–student interactions with a female tutor and 30 children aged 3, 4, and 5 years. They reported many interesting results including the fact that the younger children seemed as proficient as the older children in "solution recognition tasks," but not in "action-led-achievement tasks." For older children, the tutor's role was more of checking or confirming than was the case for younger students. In the context of DDM, Davidsen and Spector [28] analyzed the successful uses of SD-based learning environments. They found that many of the successful ILEs depended on effective pre-task preparations and instruction by the facilitator. More importantly, learning effects in these ILEs appeared highly dependent on the simulation activities-debriefing sessions and exercises.

The key role of the facilitator is to facilitate the "institutionalization of knowledge" [36]. Learners can have many experiences with the learning environments. Initially, they have no way to know which experiences are important and useful for real world situations. The facilitator has to provide this knowledge. Similar concerns have been echoed in the *assimilation paradox* [21]—self-directed learners, in the absence of help and guidance, face difficulties in assimilating the new knowledge with the existing knowledge and mental models[3]. Debriefing reviews by the

[3] Mental models are abstract representations in our mind of things and situations around us [37]. When it comes to people's decision-making in dynamic tasks, we consider mental models as the representation of "causal relationships between the variables of the task system" that a decision-maker attend to or make use of them [65]. For excellent review on mental model concept and its use in dynamic systems, please see in [48].

facilitator [28] appear to help learners overcome these difficulties and distortions and update their mental models [68]. Improved understanding of the task system then helps decision-makers to perform better in dynamic tasks [30]

Using the business simulator LEARN!, Gröbler et al. [46] conducted an experiment to operationalize task transparency in terms of provision of structural information about the underlying task system. They reported strong support for the benefits of a presentation by the facilitator a pre-task level support. Subjects were able to develop a causal understanding between the variables of the task system—a critical skill in achieving the task objective (e.g., maximizing the profitability of the firm in this task) in a dynamic task. These findings provide evidence to the lack of task transparency as a possible explanation to the results of earlier studies, where subjects performed poorly in dynamic tasks.

Human facilitation plays a key role in any learning albeit developing skills in decision-making in dynamic tasks where subjects are susceptible to develop misperceptions about the task system. In fact, a structured feedback with the help of step-by-step analysis of subjects' performance in the simulated task positively influences an understanding of the problem and the time for task completion [66]. With improved understanding of the task, decision-makers are likely to commit fewer mistakes and become efficient problem solvers.

In ILE sessions, it is customary to have some sort of debriefing reviews—where the performance of users in dynamic task is analyzed. However, to accrue the learning benefits, the outcome-based facilitation should be integrated with process-based facilitation. In fact, process-based human facilitation, that allows the users of ILEs to correct the misperception of the task they did, was shown to improve not only task knowledge and task performance in dynamic tasks but also enhance subjects' transfer learning skills [15, 84]. Provision of causal loop diagrams[4] where the relationships between key variables of the task system are described improve subjects' task performance and transfer learning [85].

Group information feedback and facilitation helps learning and decision-making in dynamic tasks [15]. Using a system dynamic model of production process in a laboratory-experiment, Borštnar et al. [15] reported that use of a simulator supports individual learning and provided group information feedback, enhances group performance. In fact, those who were supported by structured group information and process feedback were able to develop a broader view of the problem and insights into new ideas and became efficient problem solvers [24]. On the other hand, in the non-structured process with dispersed information, subjects' performance was degraded. As a better understating and development of insights about the task system is often the key learning goal of an ILE session, the role of process-based human facilitation becomes critical.

[4] A causal loop diagram (CLD) is a powerful tool used to depict the causal links between the variables of a complex task system. The casual links between any two variables are of two kinds: (1) positive causal link (i.e., A causal link from a variable X to another variable Y is positive if a change in X causes a change in Y in the same direction), and (2) negative causal link (i.e., A causal link from a variable X to another variable Y is negative if a change in X causes a change in Y in the opposite direction). For instance, in our fisheries management task, an increase in Fish Catch produces an increase in the Revenue of the firm, a positive causal link. On the other hand, an increase in Fish Catch causes a decrease in Fish Density, a negative causal link.

2.9 Summary of Empirical Evidence on Decision-Making in Dynamic Tasks

In the context of ILEs, the critical evaluation of existing research, with over 40 studies, on decision-making and learning in complex, dynamic tasks distils some important insights. Among the learners' factors, prior knowledge that is brought to the ILE-based training session helps them perform better in dynamic tasks. With increased task transparency, decision-makers can better handle dynamic tasks. Also, working in groups leads to more improved task performance and learning than compared with individual decision-makers. Finally, structured human facilitation, when provided at pre-task, in-task, and post-task levels in an ILE-based training session, helps decision-makers perform better on task performance and acquire more task knowledge. The next Chap. 3 presents an integrated process model for decision-making and learning in dynamic tasks that accounts for these critical factors.

2.10 The Insights

- The ultimate aim of any learning and training program is to help learners achieve transferable skills and ILEs are no exception.
- In dynamic tasks, consistent attention and focus by the decision-makers on achieving the stated learning goals appear to lessen the distractive cognitive demands.
- In most of the prior empirical studies on DDM and learning with ILEs, "task performance" is the major dependent variable, while in a few cases "task knowledge" and "transfer learning" are the outcome variables of the studies.
- In training sessions with ILEs, prior knowledge and experience that the learners possess and the decision strategies they adopt while performing dynamic tasks stand out as critical factors for successful performance in dynamic tasks.
- With smaller groups in ILEs, the benefits of peer-learning can facilitate improved performance in dynamic tasks.
- Human facilitation plays a key role in any learning albeit developing skills in decision-making in dynamic tasks where subjects are susceptible to develop misperceptions about the task system.

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