Improving Understanding, Learning, and Performances of Novices in Dynamic Managerial Simulation Games

A Gradual-Increase-In-Complexity Approach

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Simulations are increasingly used in training and education because of their success and their advantages as a learning method. However, it has also been observed that the dynamic complexity of simulations creates learning difficulties, and that performance tends to plateau quickly at a level well below benchmark performance. To overcome this difficulty, a gradual-increase-in-complexity approach is proposed, which suggests developing simpler versions of a simulation game that can be used as part of the training. Accordingly, the authors developed a series of inventory-management simulations and conducted an experiment. The results indicate an improvement in the success of the inventory-management simulation as a training tool. © 2009 Wiley Periodicals, Inc. Complexity 15: 31–42, 2010

Key Words: dynamic complexity; business simulation games; inventory management; cognitive load; learning curve; performance plateau; performance improvement

1. INTRODUCTION

Simulations in general, and business simulations in particular, are often used for training and education because they provide risk-free, enjoyable, realistic, and interactive learning environments [1–11]. Furthermore, simulations help participants accumulate experience rapidly by enabling them to make decisions and to see the results of their decisions in a comparatively short time [11–13]. Therefore, it is not surprising that the classroom validity of business simulations is well established and that business simulations are highly rated by the participants as a successful learning method [9, 10, 14–16].

In addition to training and education, simulations are frequently used to study learning in complex decision-
making environments [17–19]. In these studies, it is frequently observed that after an initial improvement, the performance of the participants tends to plateau at a level significantly lower1 than the corresponding benchmark performance [12, 20–22].

The pre-mature performance plateau is a natural result of the counterintuitive nature of complex dynamic systems [13, 23–25]. This “Why is understanding complex systems a difficult problem? The behavior of complex systems is often counter-intuitive” (p. 9 in Ref. 27). There is strong evidence that people often fail to understand and control the behavior of complex dynamic systems [12, 13, 20, 28–34]. Furthermore, some studies have shown that even naive do-nothing rules outperform most participants under complex dynamic conditions [12, 20, 31].4

The negative effect of complexity on human learning and performance can be explained by cognitive load theory. According to this theory, long-term memory is assumed to be limitless, and it includes everything that we have learned. On the contrary, short-term memory (working memory), which is responsible for information processing and learning, is quite limited. If the cognitive load of a task is not maintained within the working-memory capacity limitations of the trainees, they fail to deal adequately with the task, and effective learning does not take place. Therefore, the information-processing demands of a task must be managed so that they do not exceed the very limited working-memory capacity of trainees during the learning process [35–38]. However, because of their complexity, most simulation games impose information-processing demands that quickly exceed the working-memory capacity of the participants. “The barriers to learning include the dynamic complexity of the systems themselves” (p. 291 in Ref. 13).

Complexity is the source of counterintuitive behavior, cognitive load, poor understanding, and poor performance. However, it is impossible to get rid of complexity because, without complexity, it is impossible to create valid models of real systems. If the validity of a business simulation game is low, it will not be an effective learning tool. Therefore, one can conclude that the effectiveness of a simulation is highly related to the level of validity and usefulness of its underlying model structure. The extent to which the problem-relevant details of the real system are correctly reflected determines the validity of the model, and the extent to which unnecessary details of the real system are excluded from the model determines its usefulness. Therefore, there should be a good balance between model complexity and simplicity [25, 26, 39, 40].

Compared with real systems, simulations are less complex. Therefore, if a business simulation game has a valid and useful underlying model structure, it provides a more efficient learning environment than the real system itself [15, 25, 39]. For this reason alone, the effort to optimize the effectiveness of simulations is of great importance.5 However, this is not sufficient because even simulations that incorporate modest levels of dynamic complexity create understanding and learning difficulties for most people [13, 28–33]. “Improving decision making and learning in dynamic environments presents a major challenge to researchers” (p. 20 in Ref. 17).

In an attempt to overcome the stated learning difficulty, this research proposes a gradual-increase-in-complexity approach which is based on manipulating the level of complexity itself. It is suggested here that understanding and performance in a simulation game can be improved by developing simpler versions of that game and using them as a part of the training. The level of dynamic complexity of the simulation game can be gradually decreased to obtain less complex versions. Trainees should first play the original, most complex version of the simulation a few times. After that, they should continue to play the simpler simulations, starting from the least complex. Finally, they should play the original, most complex version of the game a few more times. Playing the most complex version of the simulation first will increase the motivation to learn from the simpler ones. Moreover, participants will be able to recognize their own improvement at the end of the learning process. Conversely, if they start by playing the simpler simulat-

1“Lower performance” means lower profit in profit maximization tasks, but higher cost in cost minimization tasks.

2The benchmark performance in some cases is optimum, but in most cases, it is hard or impossible to obtain the optimum performance, and a good benchmark performance is generated by using an appropriate decision heuristic. Moreover, sometimes researchers prefer to generate poorer benchmarks by using simple behavioral decision-making rules to demonstrate the weaknesses of human decision-making processes by comparing human success with the success of these naive rules [12, 20].

3It should be kept in mind that even elementary dynamic models are capable of producing complex behaviors [25, 26].

4Some of these studies have also reported a strong relationship between complexity and performance. As complexity increases, the performance of the participants deteriorates relative to the corresponding benchmark performance [12, 13, 31–34].

5Sayesel and Barlas suggest a model simplification process to increase the quality, usefulness, and understanding of models. The simplification process continues until the minimum level of complexity that is necessary to explain the dynamics of interest is achieved [40].
tions right away, their motivation will be less, and they will fail to appreciate the learning process. The gradual-increase-in-complexity approach suggests playing the simpler versions of the original simulation by starting from the simplest version and moving to more complex versions to support understanding and proper mental-model (schema) formation. Decreased cognitive load supports mental-model formation, and once a proper mental model of a task is formed, that task imposes less cognitive load on the working memory of the trainee, which further promotes understanding and learning [35–38, 41]. Accordingly, to test the proposed approach, the researchers developed a simple inventory-management simulation game with a single decision variable, created simpler versions of this game, and conducted an experiment. In the following sections of this article, the game and its simpler versions are explained, and the results obtained from the experiment are discussed. According to the results, the gradual-increase-in-complexity approach contributes to the understanding of the trainees, which is reflected in an improvement in their performances.

2. INVENTORY MANAGEMENT GAME

An inventory-management game was developed for use in this study. Each participant is given a separate user name and password. After logging in, each user reads the instructions page given in Appendix A, which explains the underlying complex structure in full detail. After the participant clicks on “Continue...” (see Appendix A) the main game screen appears (see Figure 1).

Then, the participant starts to enter decisions by clicking on the “Simulate” button and continues to enter further commands until the message, “Simulation is complete, click to restart,” appears (see Figure 2).

The minimum total cost (benchmark) that can be obtained from the game is $198. The optimum run6 that minimizes the total cost is shown in Figure 2. Several example inventory dynamics (inventory behavior over time) produced by different participants are also shown in Figures 3 and 4. The benchmark (Inventory 1) is shown in both figures.

6Each run is a completed game.
to facilitate comparison, because the vertical scales of the
two figures are different from each other. The corresponding
total costs for the second (Inventory 2), third (Inventory 3),
and fourth (Inventory 4) runs are respectively $2714, $1848,
and $1438 for Figure 3, and $924, $766, and $361 for Figure 4.
Although the total cost changes dramatically between
different runs, all the inventory dynamics exhibit the same
characteristic oscillatory behavior. In only a few runs, which
are not presented here, participants did not obtain oscilla-
tions. The reason for this was simply that, in these runs, the
participants were not actively engaged in controlling the in-
ventory, but simply entered a constant value throughout the
simulation. In general, in inventory dynamics, a high total
cost results from a high amplitude of oscillations, and simi-
larly a low total cost results from a low amplitude of oscilla-
tions. The amplitude of the oscillations depends on the de-
cision heuristic\(^7\) used in managing the inventory. A decision

\(^7\)For behavioral decision heuristics, see for example [25, 42, 43].

heuristic that ignores the amount of existing orders yet to
arrive increases the amplitude of the oscillations. Moreover,
aggressive ordering policies also contribute to the ampli-
tude. Similar types of oscillatory behavior have also been
reported by several other researchers [28–31, 34, 44].

One might expect participants to obtain low costs from
the very beginning because the model structure is explained
in full detail and the future customer demand is known
before participants start to play the game. In addition, cus-
tomer demand does not fluctuate; it is equal to 10 items/
week until week 3 and 20 items/week thereafter. Although
everything looks obvious, the dynamic complexity of the
underlying structure still overwhelms people when they play
the game for the first time. Therefore, none of the participants
was able to obtain the minimum cost in the first three runs.

3. THE FOUR SIMPLIFIED VERSIONS OF THE GAME
The simplified versions of the game were obtained by
gradually decreasing the structural complexity of the in-
ventory-management simulation as follows:
The fourth simplified game is obtained from the original game by changing the dynamic “Shipment Capacity” to a constant and setting it equal to 30 items/week.

The third simplified game is obtained from the fourth by removing the limit on “Shipment Capacity.” In this version of the game, the supplier immediately ships the order of the participant, even if it is extremely high.

The second simplified game is obtained from the third by decreasing the shipment delay from 4 weeks to 1 week.

The first simplified game is obtained from the second by completely removing the shipment delay. In this version of the game, orders that are placed arrive as soon as the “simulate” button is clicked.

FIGURE 3

Example inventory dynamics generating comparatively high total cost values.

FIGURE 4

Example inventory dynamics generating comparatively low total cost values.
The instructions page (Appendix A) was also updated to reflect these changes, and the changes were underlined to make it easy to recognize them. Note that the main game screen remains unchanged except for “Shipment Capacity,” which was removed from both the table and the graph in the first three simplified versions of the game. The game screen for the fourth simplified version of the game is exactly the same as the original game screen. By keeping the game screen as close to its original version as possible, it was hoped to eliminate any effects that might arise from the way the variables were presented to the participants.

4. EXPERIMENTAL DESIGN

In the first part of the study, all participants were asked to play the original version of the game seven times. The goal was to minimize the total cost, but no specific target value was given. In the second part of the study, participants were supposed to play the four simplified versions of the inventory management game, starting with the simplest one. The simplified versions of the game were presented in such a way that their complexity gradually increased from one simulation to the next. Participants were asked to play the game until they managed to achieve the explicitly stated total-cost values for each simplified simulation. Note that the minimum total-cost values change as the complexity of the simulation changes. For the first, second, third, and fourth versions of the simplified game, the minimum total-cost values are $0, $0, $30, and $40, respectively. Participants were given these values so that they could be sure about the decision heuristics they developed. In the third part of the study, they were asked to play the original version of the game twice more. Again, the goal was to minimize the total cost, but a specific target value was not given. Finally, when participants finished playing the simulations, they were given a questionnaire (see Appendix B).

5. RESULTS

Twenty-one people participated in the study. Although they were asked to play the game seven times in the first part of the study, only a few did so; most participants played the game more than seven times. When questioned, they said that they were not counting their runs and also that they were expecting a notice to stop, something that should be considered in future studies. Similarly, they were asked to play the game twice in the third part. However, many participants played more than twice. No participant played the game fewer than seven times in the first part and fewer than two times in the third part. Summary statistics on the number of completed runs are given in Table 1. Note that the incomplete runs\(^8\) are excluded from this table. The reason for excluding the incomplete runs is that it would not be possible to compare the total-cost values generated over fewer than 40 simulated weeks with the values generated at the end of 40 simulated weeks.

The natural logarithms of the total-cost values generated by the participants were then calculated and their averages were plotted for the first seven runs of the first part of the study (see Figure 5). It can be seen from the first part of Figure 5 that after an initial improvement, the average value of the natural logarithms of the total-cost values levels off after the fourth run, which is consistent with the literature which states that learning and performance in dynamic decision-making quickly level off at suboptimal values [12, 20–22]. Paich and Sterman reported that performance in their experiment saturated at the fourth and fifth runs [12]; see also Figure 3 in Ref. 22. To see the effect of part 2 on the learning curve, the averages obtained from the first two runs of part 3 were added to Figure 5 as the eighth and ninth runs.

Figure 5 suggests that part 2 contributed to the learning curve and that the gradual-increase-in-complexity approach improves the learning process. However, two criticisms might be made at this point:

- The improvement observed in part 3 might be caused not only by part 2, but might also reflect experience from the additional runs\(^9\) performed by the participants who played more than seven times in part 1.
- The improvement observed in part 3 might have been caused simply by more experience in playing the game, and if the participants had played more games in part 1 instead of playing the simple simulations in part 2, they might have achieved similar results.

The authors believe that they can respond to these criticisms. First, in previous studies, after the leveling-off of performance, no further improvement was observed [12, 20–22]. Therefore, part 2 (playing simpler versions of the same simulation) should have played an important role in obtaining the effect observed in Figure 5. The authors also carried out a linear regression analysis to investigate if there is any support for the criticisms in the collected data. The regression model is given below:

\[ y = b_0 + b_1 x_1 + b_2 x_2 + \ldots + b_n x_n \]

\(^8\)The number of incomplete runs: None in part 1, 7 in part 2 (2, 3, 1, and 1 runs, respectively, in the first, second, third, and fourth simplified simulations), and 3 in part 3.

\(^9\)Five participants performed 7 runs, four performed 8, six performed 9, one performed 10, two performed 11, one performed 12, one performed 15, and one performed 24 runs in part 1; see also Table 1.
\[ \ln(TC) = \alpha + \beta_1 \times \text{Run} + \beta_2 \times \text{Duration} + \beta_3 \times P2\text{completion} + \beta_4 \times P2\text{runs} + \beta_5 \times \text{lowTCinP1} + \beta_6 \times \text{Interaction} \]

where \( \ln(TC) \) is the natural logarithm of the total-cost value generated in a run, \text{Run} is the run number, Duration is the time that took a participant to complete a run, P2completion\(^{11} \) indicates whether a run was carried out before or after part 2, P2runs\(^{12} \) is the number of runs carried out in part 2 before the run under consideration, lowTCinP1\(^{13} \) indicates whether or not a particular run belongs to a participant who managed to achieve low total-cost values in part 1, and Interaction is obtained by multiplying the values of P2completion and lowTCinP1.

It is known that initially the total cost will tend to decrease from one run to the next. However, because of leveling-off of performance, the total-cost values were not expected to change after the fourth run. To remove the effect of the initial improvement, the first four runs of all participants were not included in the regression analysis.\(^{14} \)

The regression analysis produced the results given below:

- The intercept of the regression model is significant (\( \alpha = 7.18060; P\text{-value} < 0.0001 \)).
- Run number was not found to have a significant effect on the natural logarithm of the total-cost values (\( \beta_1 = 0.00384; P\text{-value} = 0.745 \)), which addresses the two criticisms made above; after a certain point (i.e., after first initial 4 runs), carrying out more runs does not improve performance.
- It appears that participants who took more time for their runs generated higher costs (\( \beta_2 = 0.00115; P\text{-value} < 0.0001 \)). Actually, this observation represents only the strong correlation between the total cost and the duration of a run, because these two variables are both influenced by another variable, the cognitive load of the task for that person. It is natural that, if cognitive load is high for a participant, that participant will complete a run in a relatively longer time and with a higher total cost.
- P2completion is significant (\( \beta_3 = -0.75589; P\text{-value} < 0.001 \)). Most participants achieved lower costs after completing part 2, which supports the present claim that the gradual-increase-in-complexity approach improves understanding, learning, and performance.
- P2runs does not have a significant effect on costs (\( \beta_4 = 0.00283; P\text{-value} = 0.812 \)), which means that it is not the number of runs that affects performance, but the completion of part 2.

**TABLE 1**

The Summary Statistics on the Number of the Completed Runs

<table>
<thead>
<tr>
<th></th>
<th>First Part</th>
<th>First Simple Simulation</th>
<th>Second Simple Simulation</th>
<th>Third Simple Simulation</th>
<th>Fourth Simple Simulation</th>
<th>Third Part</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total No. of runs</td>
<td>204</td>
<td>49</td>
<td>64</td>
<td>106</td>
<td>38</td>
<td>93</td>
</tr>
<tr>
<td>Average No. of runs</td>
<td>9.71</td>
<td>2.33</td>
<td>3.04</td>
<td>5.04</td>
<td>1.80</td>
<td>4.43</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>3.82</td>
<td>1.39</td>
<td>3.41</td>
<td>4.77</td>
<td>1.75</td>
<td>3.88</td>
</tr>
<tr>
<td>Median</td>
<td>9</td>
<td>2</td>
<td>2</td>
<td>2</td>
<td>1</td>
<td>3</td>
</tr>
<tr>
<td>Mod</td>
<td>9</td>
<td>2</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>2</td>
</tr>
</tbody>
</table>

\(^{10} \)The natural logarithms of the total-cost values obtained in part 3 were added to the values obtained in part 1. Accordingly, if someone performed \( n \) runs in part 1, the \( (n + m) \)th run of that person corresponds to the \( m \)th run he performed in part 3.

\(^{11} \)P2completion is equal to 0 for part 1 runs and 1 for part 3 runs.

\(^{12} \)P2runs takes on two different values for each participant; if a run belongs to part 1, this variable takes on a zero value, and if a run belongs to part 3, this variable takes on a value equal to the total number of the runs completed in part 2 by that participant.

\(^{13} \)lowTCinP1 is equal to 1 for six of the participants who managed to obtain at least one cost lower than $300 in part 1 and is equal to 0 for the rest.

\(^{14} \)21 participants generated 297 data points; 84 of these belong to the first four runs in part 1, which were excluded. Therefore, only 213 of them were included in the regression analysis.
lowTCinP1 is significant ($\beta_5 = -1.36126; P\text{-value} < 0.0001$), which means that the participants who managed to obtain at least one cost lower than $300 in part 1 generally obtained lower costs than the rest of the participants. This suggests that they did not obtain these low costs simply by luck, but through better understanding, which was also reflected in their subsequent runs.

- Interaction between P2completion and lowTCinP1 is significant ($\beta_6 = 0.72117; P\text{-value} < 0.001$). Note that the size of $\beta_6$ is almost equal to $\beta_3$, which neutralizes the effect of P2completion for those who had already managed to achieve low costs in part 1. This means that part 2 did not improve the performances of these participants, either because they had already achieved the benchmark value, or because they obtained very low costs which were close to the benchmark. Note that the inventory-management game used in this study is a comparatively simple one with respect to many other business simulations. Therefore, some of the participants were expected to achieve the minimum cost.

After removing the independent variables that have no significant effect in the previous regression model, the new regression model becomes:

$$\ln TC = \alpha + \beta_1 \times \text{Duration} + \beta_2 \times \text{P2completion} + \beta_3 \times \text{lowTCinP1} + \beta_4 \times \text{Interaction}$$

The new values of the parameters can be listed as:

- $\alpha = 7.20753; P\text{-value} < 0.0001$
- $\beta_1 = 0.00115; P\text{-value} < 0.0001$
- $\beta_2 = -0.69980; P\text{-value} < 0.0001$
- $\beta_3 = -1.34960; P\text{-value} < 0.0001$
- $\beta_4 = 0.70737; P\text{-value} < 0.001$

The overall regression model is statistically significant ($P\text{-value} < 0.0001$). The value of the coefficient of determination ($R^2$) is calculated as 0.44008; adjusted-$R^2$ is equal to 0.42931. The regression model explains 44% of the variability in the data, but 56% of it remains unexplained, which suggests that there is a high variability in the performances of the participants. This is not uncommon. Human behavior, especially in a complex dynamic environment, can generate highly variable outcomes. Therefore, $R^2$ of this size is valued in behavioral sciences [45].

The authors claim that the effect of the simple simulations on performance improvement would have been stronger without the observed tendency among the participants to give up intentional control of the inventory when they felt that the current run was not going to be successful. In these cases, participants aimlessly clicked on the simulate button just to finish the game. This tendency was especially strong in part 3. As a result, some of the participants created extremely high costs in the third part, even much higher than the costs that they generated in part 1 (e.g., $4195, 4902, 2167, 5587$). These values do not reflect the level of understanding of the participants. Moreover, they decreased the size of the effect shown in Figure 5. Despite this, the authors did not eliminate the complete runs with a run number greater than or equal to five, even the extreme ones noted above, and used the data generated after the first four runs without modification in all the analyses. Even under these unfavorable conditions, the improvement shown in Figure 5 is statistically significant.

There is no support for the two criticisms in the simulation data. On the contrary, data supports the claim that the gradual-increase-in-complexity approach is successful in improving understanding, learning, and performance in dynamic decision-making environments. Note that the natural logarithm of the optimal total cost value ($198$) is $3.288$. It is obvious that there is room for further improvement (see Figure 5).

6. QUESTIONNAIRE DATA

The answers of the participants to the questions given in Appendix B are summarized in Tables 2 and 3. A numerical value

15As stated before, to remove the effect of the initial improvement, the first four runs of all participants were not included in the regression analysis.

16The parameter ($\beta_2$) in the regression equation, which reflects the effect of part 2 completion (P2completion) on the natural logarithms of the total cost values (lnTC), is statistically significant.
was assigned to each possible answer, as shown in the tables. Most of the participants had little or no prior experience in inventory management itself or in inventory-management simulations (questions 1 and 2 in Table 2). On average, participants thought that part 1 made some contribution (question 3 in Table 2) and part 2 a substantial contribution (question 4 in Table 2) to their understanding of how to perform in part 3 and that part 2 contributed more than part 1 (questions 3 and 4 in Table 2 and question 5 in Table 3).\textsuperscript{17,18} Except for one person, participants enjoyed playing the simulations to various degrees (question 6 in Table 2). Except for two people, they believed that they could make very little or some use of the insights gained from playing the game (question 7 in Table 2). It is natural to expect that the participants would be able to some degree, to transfer the insights from the game into their daily lives, because the elements of dynamic complexity\textsuperscript{19} that are present in the simulation game, such as delays, are involved in most decision-making tasks as well.

As stated in the introduction part of this article, simulations are highly rated by the participants as a successful learning method. The participants in this study rated the simpler versions of the inventory management simulation even higher than the original version of the simulation itself (results of questions 3, 4, and 5). Therefore, the questionnaire data supports the claim that the gradual-increase-in-complexity approach, playing simpler versions of the simulation, helps developing understanding and achieving better results on the most complex version of the task itself.

**7. CONCLUSIONS**

Simulations are very helpful in training people in complex dynamic decision-making. People playing simulations often gain experience quickly and improve. However, it is also known that this improvement tends to stop prematurely at suboptimal levels after a few initial runs. The main reason for this learning difficulty is the dynamic complexity of the decision-making task itself. To overcome this difficulty, the gradual-increase-in-complexity approach has been proposed here.

In this research, the authors developed a series of inventory-management simulations and conducted an experiment. The results of the experiment show that an

### Table 2

<table>
<thead>
<tr>
<th>Letter and Value</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
<th>Q4</th>
<th>Q5</th>
<th>Q6</th>
<th>Q7</th>
</tr>
</thead>
<tbody>
<tr>
<td>a−0</td>
<td>14</td>
<td>13</td>
<td>2</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td></td>
</tr>
<tr>
<td>b−1</td>
<td>5</td>
<td>3</td>
<td>4</td>
<td>2</td>
<td>1</td>
<td>6</td>
<td></td>
</tr>
<tr>
<td>c−2</td>
<td>1</td>
<td>4</td>
<td>9</td>
<td>5</td>
<td>8</td>
<td>13</td>
<td></td>
</tr>
<tr>
<td>d−3</td>
<td>1</td>
<td>1</td>
<td>5</td>
<td>8</td>
<td>9</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>e−4</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>6</td>
<td>2</td>
<td>0</td>
<td></td>
</tr>
<tr>
<td>Average</td>
<td>0.476</td>
<td>0.667</td>
<td>1.952</td>
<td>2.857</td>
<td>2.476</td>
<td>1.524</td>
<td>1.524</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.814</td>
<td>0.966</td>
<td>1.024</td>
<td>0.964</td>
<td>0.928</td>
<td>0.680</td>
<td>0.680</td>
</tr>
<tr>
<td>Confidence interval (95%) for the population mean</td>
<td>Lower</td>
<td>0.106</td>
<td>0.227</td>
<td>1.486</td>
<td>2.419</td>
<td>2.054</td>
<td>1.214</td>
</tr>
<tr>
<td></td>
<td>Upper</td>
<td>0.847</td>
<td>1.106</td>
<td>2.418</td>
<td>2.396</td>
<td>2.899</td>
<td>1.833</td>
</tr>
</tbody>
</table>

\textsuperscript{17} Paired samples t-test; $H_0$: $\mu_4 \neq \mu_5$; $H_a$: $\mu_4 > \mu_5$; $H_0$ is rejected; $P$-value < 0.01.

\textsuperscript{18} One sample t-test; $H_0$: $\mu_5 \neq 0$; $H_a$: $\mu_5 > 0$; $H_0$ is rejected; $P$-value < 0.01.

\textsuperscript{19} The main elements of dynamic complexity are accumulation processes, feedback loops, time delays, and nonlinearities [12, 13, 31–33, 46–48].

### Table 3

<table>
<thead>
<tr>
<th>Letter and Value</th>
<th>Q5</th>
</tr>
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<tbody>
<tr>
<td>a−(−1)</td>
<td>4</td>
</tr>
<tr>
<td>b−1</td>
<td>14</td>
</tr>
<tr>
<td>c−0</td>
<td>3</td>
</tr>
<tr>
<td>Average</td>
<td>0.476</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.814</td>
</tr>
<tr>
<td>Confidence interval (95%) for the population mean</td>
<td>Lower</td>
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<tr>
<td></td>
<td>Upper</td>
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</tbody>
</table>
improvement in the learning curve is possible. According to regression analysis, the observed improvement is statistically significant, and therefore, the gradual-increase-in-complexity approach has been found to be successful. Furthermore, the questionnaire data obtained from the participants were also supportive of this approach. In future studies, the authors plan to test the approach further with other business simulation games. Another concern for future studies is the remaining potential improvement in the learning curve.

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REFERENCES

APPENDIX A: THE INSTRUCTIONS PAGE

Instructions

In this simulation game, the aim is to manage the level of your inventory to minimize the total cost associated with storage and delayed deliveries.

You receive items from your supplier and you deliver items to your customers. The amount of items that you receive is controlled by you via placing “orders,” which is the only decision variable in this game. You can order as many items as you want. However, you cannot cancel orders once they are placed, which means that any negative value that you enter will automatically be treated as zero.

It normally takes 4 weeks for your orders to be shipped to you. However, you should keep in mind that your supplier has many customers and she can dedicate only a limited shipment capacity to you. If you go above this limited capacity, your orders will further be delayed till your supplier adjusts the capacity.

Your inventory can take positive or negative values. If your inventory is positive, this means that you need to store items and pay for the storage, which is $1 per item per week. If your inventory is negative, this means that you have unfulfilled demand. According to the agreement that you have with your customers, demand should be fulfilled immediately in the week that it appears. Otherwise, you pay them $1 per item per week for the delayed deliveries. When your inventory is zero, no cost is incurred. Therefore, the ideal level for your inventory is zero.

Note that the customer demand is 10 items per week till week 3 and 20 items per week thereafter.

You need to make decisions starting from week 1 until the game ends at week 40. The “Total Cost” generated at the end of the game will be your score. Your aim is to minimize the total cost by managing your inventory as close as possible to its ideal level.

Best of luck!
(Note that you can always visit this page during the game).

Continue…

APPENDIX B: THE QUESTIONNAIRE

1. How much experience have you had with inventory management prior to participating in this study (including any courses you have taken on the subject)?
   a) None at all, b) Very little, c) Some, d) Quite a lot, e) Very much

2. How much experience have you had playing with inventory management simulations prior to participating in this study?
   a) None at all, b) Very little, c) Some, d) Quite a lot, e) Very much

3. To what extent did part 1 of the study help you to improve your understanding of how to perform in part 3?
   a) Not at all, b) Very little, c) Some, d) Quite a lot, e) Very much
4. To what extent did part 2 of the study help you to improve your understanding of how to perform in part 3?  
   a) Not at all, b) Very little, c) Some, d) Quite a lot, e) Very much  
5. Which part was more helpful to you in improving your understanding of how to perform in part 3?  
   a) Part 1, b) Part 2, c) Both part 1 and part 2 had almost equal effects  
6. To what extent did you enjoy playing these simulations?  
   a) Not at all, b) Very little, c) Some, d) Quite a lot, e) Very much  
7. To what extent do you think that you will be able to use your insights from the study in your daily life?  
   a) Not at all, b) Very little, c) Some, d) Quite a lot, e) Very much