

# Visualization, Serious Games and Decision Making

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**Abstract:** One of the most important objectives of serious games is to detonate behavioral changes of participants. Serious games generate engagement, they are meaningful, entertaining, and immersive. However, when the game represents a complex system, it contains a great number of variables and the relationship between its decision components are not entirely clear. Consequently, it is necessary to offer a set of tools that increase the data visualization of the players and help in the decision-making process must be provided. In our university, logistics professors have designed a simulator for logistics decision making. On the one hand, the game has gained acceptance from the student community, but on the other hand, several students do not accomplish a satisfactory performance. Therefore, these students fail to notice lots of variable interrelationships in the game, and they do not develop the skill required to follow a good decision-making process. The goal is two folded. On the one hand, the improvement of the participant's comprehension of a complex logistical system must be reached. On the other hand, the clarity on the decision-making process has to be laid out. A set of visualization support tools were created to accomplish those objectives. Neither of the tools aim to influence the decision-making process nor to show decision alternatives to the participant, but to highlight a few key performance indicators, constraints, and data that the students can use when making the decisions. In this paper it is presented how the participants have improved their understanding about the logistic system represented in the game, when the support tools are used. Moreover, their motivation has increased, they are more involved and committed to learn. Overall, their decision-making strategies have been modified and they have shown a better comprehension of the game structure. This paper contributes to underline the importance of visualization in student's learning, considering that currently big data, industry 4.0, as well as internet of things have gained a significant relevance in our everyday life. The design of strategic games involving these new variables are necessary. The more complex a system, the greater the number of visualization tools to strengthen the comprehension of the system are required.

**Keywords:** Higher Education, Educational Innovation, Visualization, Serious Games, Logistics Education

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## 1. Introduction

The decision-making process frequently occurs in our modern life. Decision making is one of the key processes within the business environment and in all organizations. Decision consequences have a direct impact on the structure and in the profit of a company. Competitors and the demands of the market lead to continuous company innovation. Strategic decisions must always be made to improve their reputation. Besides being effective and agile, decisions must comply with the least margin of error, since a bad decision made at the wrong time with lack of context analysis can have irreversible consequences for the company.

Many studies have been carried out on the decision-making processes as well as on the different resources that are used for improvement. Data visualization and data plotting are useful tools in decision making, since they summarize large data sets. Moreover, they show trends, outliers, patterns, and clusters, among others.

This article presents a Logistic Simulator (LOST), which is a game that simulates a company where the participants make a significant number of logistical decisions. This game has been used in several courses and important results in the acquisition of knowledge, motivation, and the development of various skills such as self-study (Pacheco 2022) have been obtained. A data visualization and an analysis tool have been developed to improve the decision-making of the students who participated in this game. The influence of data visualization on LOST player's decision making is also included in this article.

## 2. Review of Literature

In recent years, the use of serious games has increased. In serious games, the main objective goes beyond fun or entertainment, they have a training purpose that leads to the acquisition of skills. These types of games have been used in a wide range of sectors such as the military sector, the health industry, the educational system and the corporate environment, among others. Serious games for educational purposes have a positive impact as it

provides an effective strategy to engage students in learning activities and stimulate cognitive processes such as information recognition, deductive/inductive reasoning, and problem-solving skills (Minović et al, 2015; Pacheco 2022; Almeida 2019).

Serious games may be of interest in the development of 21st century skills such as reaction speed, multiple attention spans, relational aptitude, high achievement motivation, greater tolerance to frustration, ability to take risks, to solve problems and to make decisions (Romero & Gebera 2012). (Almeida 2019) proposes the use of a serious games to assess and to develop emotional intelligence skills.

To name some authors such as (Laamarti et al, 2014; Vlachopoulos & Makri 2017; Zhonggen 2019; Roedavan et al, 2021) who present reviews on serious games in areas such as education, well-being, advertising, cultural heritage, interpersonal communication, and health care. (Pacheco 2022) introduces a serious game to teach logistical concepts. This author presents evidence that the game has an important influence on the motivation of students, on the development of student commitment, and on their self-directed learning. (Sierra 2020) states that a student-learning performance expectancy is essential to accept serious games.

Serious games can be used not only to teach, but also to measure knowledge acquisition after playing, presenting an empirical study based on data science (Fernández et al, 2020).

In general, serious games not only provide an interesting amount of data to the player in order to select strategies and to make decisions, but also to the teachers or to the managers so that they can monitor and evaluate the player's performance or learning. The way in which the data is presented to the player or the teacher, enters the field of visualization. (Minović et al, 2015) present a visualization tool, associated with a game, that allows them to monitor student learning in real time allowing them to react and to influence the general learning process.

Visualizations incorporate design options for data access, data transformation, visual representation, and interaction. To interpret a static display, a person must identify the correspondences between the visual representation and the underlying data (Cottan et al, 2012). Researchers have tested taxonomies of information visualization techniques (Cavaller 2021; Ruys 2020; Cottan et al, 2012; Daassi et al, 2005) so that implementers can quickly identify various techniques that can be applied to their domain of interest.

In the process of searching, interpreting, and comparing data, data visualization plays a crucial role. The increased use of computational tools in the teaching-learning processes and the rise of big data have made data analysis an essential component of educational technology. In the context of serious games, the development and the integration of learning analytics has not yet reached its full potential. (Vidakis et al, 2019) presents a library that seeks to capture and simplify data in the context of a serious games. Data visualization can be used transversally as a tool in both data formalization and data analysis processes, being one of the most powerful mechanisms for autonomously exploiting and analyzing the implicit meaning in the data. The pros of visualization are the sharing of knowledge by externalizing internal understanding, the improvement of the thinking ability and the formulation of new ideas. Visualization can also give a better understanding of relationships (Li et al, 2016). (Lowe & Matthee 2020) have performed a systematic review of the literature, identifying the requirements of visualization tools, classifying them into six groups: dimensionality reduction, data reduction, scalability and readability, interactivity, rapid retrieval of results, and user assistance.

In contemporary society, decision makers are daily faced with complex problems. People can make quick and accurate decisions if they have access to all the relevant information. Various information systems can help decision makers in such an effort presenting an adequate and understandable visualization approach in an appropriate way (Burnay et al, 2019; Po et al, 2020). Similarly, (Park et al, 2021) have analyzed 16 studies in which they found that visualization seems to bring advantages by increasing the amount of information delivered reducing the cognitive and the intellectual burden to interpret the information for decision making. Data visualization can also be misleading. If the correct data is not properly presented, nonexistent conclusions can be superficially drawn. Therefore, data visualization should primarily be about presenting good data in an unbiased way (Benoit 2019; Park et al, 2021).

### 3. Logistic Simulator – Data Hound and Visualizations

LOST is a business game with an emphasis on making decisions about the logistic operation of a company. The game is immersed in a platform aimed to the teaching of logistics called the "GOAL Project." When students enter the platform and the game, they see a series of videos that explain the game's operation, the logic, and the purpose. Upon entering LOST, they receive a set of randomly generated data with the same degree of difficulty as of their classmates. There are five scenarios on the platform, each with an increasing degree of difficulty. Each scenario also involves a higher number of decisions that the players must make.

Students can play the game as many times as possible, but there are regular deadlines to reach specific pre-established goals. These dates regularly depend on the policies of each course. Within the game, several indicators are visible to students. However, teachers have observed that if the students do not have enough knowledge, they may have difficulties interpreting the indicators or establishing strategies to correct the system's performance. In addition to this series of indicators (which are also visible to teachers), each of the player's decisions is stored in a database that the teacher can review, if necessary, to suggest various strategies to the students that might let them have better game results. In the first version of the game, there were some videos with suggestions so that the students who were playing it could obtain good results.

Students make empirical decisions on the number of the produced items based on the data obtained in each simulator turn. Some of the included tasks are the counting of required raw materials, the analysis of the quality of the materials, the choice of the supplier and how to transport the items to the store. The student's challenge is to maximize the profits on each turn. This task is the result of the analysis of the supply versus the demand, the costs of the raw materials and the transportation, which can face unforeseen scenarios in the game.

The game also contains a "leaderboard" in which students compare their performance with other class or team members. When the objectives of a scenario are achieved it is possible for students to access a new scenario that will contain new variables or more complex situations in which they must make even more decisions. Table 1 shows a short description of the different scenarios. All scenarios contain problems related to logistics issues, and all of them include elements of forecasting, inventory, transportation, production management, and supplier selection. However, the complexity of the situations and the objectives to be achieved become increasingly difficult. Undisplayed data is presented in .xls or .csv files. which cannot be analyzed immediately and clearly.

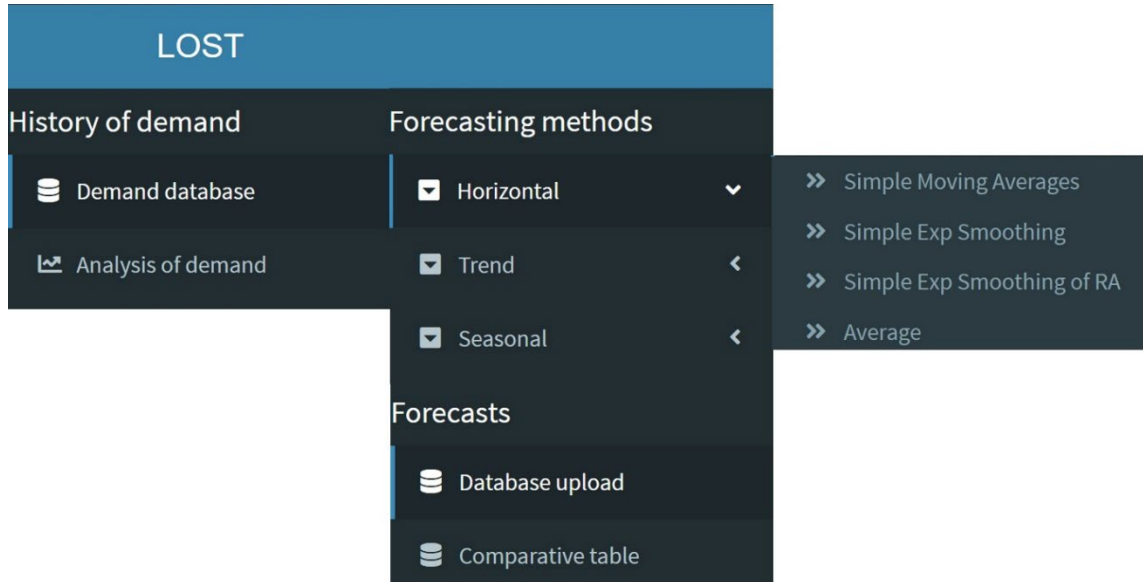
**Table 1:** Characteristics of the game scenarios.

Characteristics	Game Scenarios				
	1	2	3	4	5
Number of factories	1	1	1	1	2
Number of stores	1	1	3	3	5
Volume Discounts	x	✓	✓	✓	✓
Large transportation vehicles	✓	✓	✓	✓	✓
Small transportation vehicles	x	✓	✓	✓	✓
Single transportation route	✓	✓	x	x	x
Multiple transportation routes	x	x	✓	✓	✓
Defective production	x	✓	✓	✓	✓
Possibility to acquire new machinery	x	x	✓	✓	✓
Overtime	x	✓	✓	✓	✓
Variable prices of raw materials	x	x	x	x	✓
Machine breakdowns	x	x	x	x	✓
Change of price of finished products	x	x	x	x	✓
Contracts with customers	x	x	x	x	✓

The application is named Data Hound and Visualizations (DHV) is designed in the R programming language in its 4.1.2 "Bird Hippie" version (R Core Team, 2021). It runs and it is launched through a graphical interface through shiny packages (Chang et al, 2021) and a shiny dashboard (Chang & Borges 2021). The application runs from its own server and can be accessed from any web browser.

### 3.1 Structure of the Data Hound and Visualizations

The structure of the application is a variation of the methodological proposal of the seven steps for decision making by Flores, Molina, Alvarez (2020). The Data Hound and Visualizations (DHV) menu was designed focused on the 4 final steps of this methodology. The user can freely navigate through each stage, but a completion of each section in order to obtain the desired results is required. In Figure 1 the three sections of the menu and some subsections are shown.



**Figure 1:** Data hound and visualizations (DHV) main menu.

In the History of demand stage two sections are found. In the first section, data obtained from LOST is loaded, in second section, a first interactive graphical analysis is carried out. A summary is given for each of the game products. Given the structure in which DHV was programmed, it is easily adaptable to any number of products (variables) and records (observations). For the purposes of this work, it was adjusted to 8 products (variables) and to 104 weeks (observations). The second part of the menu consists of the Forecasting Methods, we will analyze 3 types of methods, each of which is made up of various methods so that the user can select the one that best fits the data. There are 9 methods available, each with its inputs, outputs and interactive graphs.

The Forecasts section is described in detail in section 3.3. Visualizations, scatter plots for time series and pivot tables were used for product analysis. An interactive dashboard, composed of inputs, calculated values according to user data and donut graphs, was used for the decision-making of the number of produced items.

### 3.2 System Client – Server

The application is made up of a client-server structure, which takes as input the data obtained from LOST. Once a level is completed, the output is shaped by a series of resources that will be used as guides for decision making. Users can download their respective game data to be uploaded to DHV.

Users access DHV through a web browser. Given the purpose of this tool, it works in parallel with LOST. All the data required for the DHV is obtained from LOST. As stated in the menu description of the application, the first step is to upload the Demand file. In Figure 2 the processing diagram of the DHV system is shown.

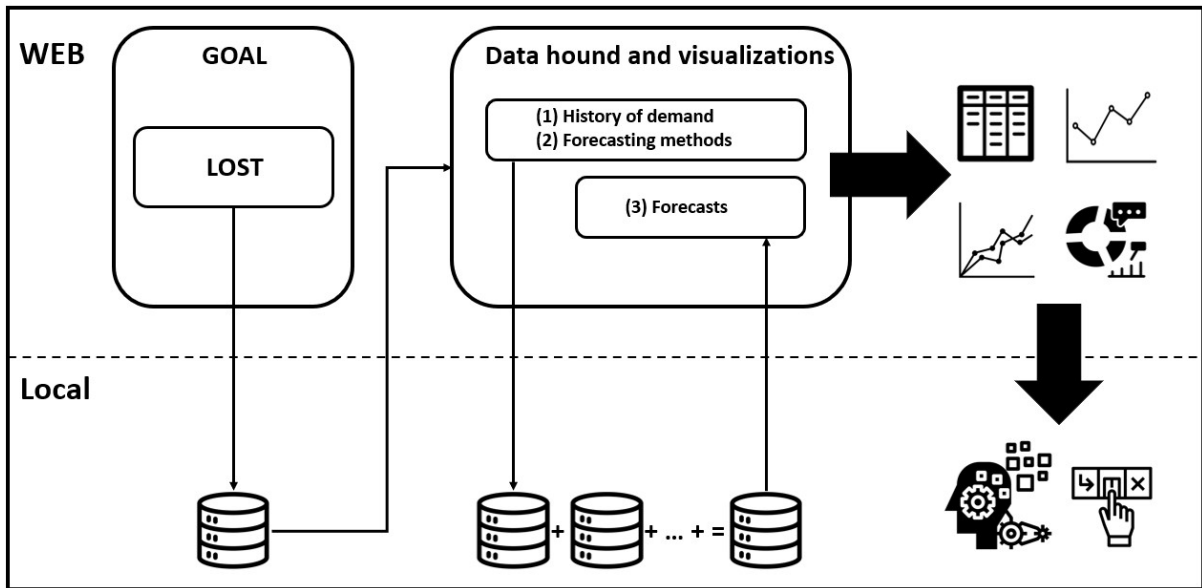


Figure 2: Data Hound and Visualization operation diagram.

### 3.3 Visualizations

The use of visualizations is a crucial part of DHV. Visualizations are a support to the decision-making process; they are not intended to decisively influence the final decision of the users. The tables, the graphs and the indicators were selected to highlight the key aspects when playing LOST.

Figure 3 shows the structure of the nine forecasting methods, which contain a comparative graph between demand data and forecast data according to the selected method (left top). In the lower left part, the graph of the probability of satisfying the demand in the following period is shown. The product selector and the input parameters of the selected method are presented in the upper right part, as well as the corresponding input for the method to be used. Descriptive statistics and precision measures appear in the table to the right, as well as downloadable data for the selected method.

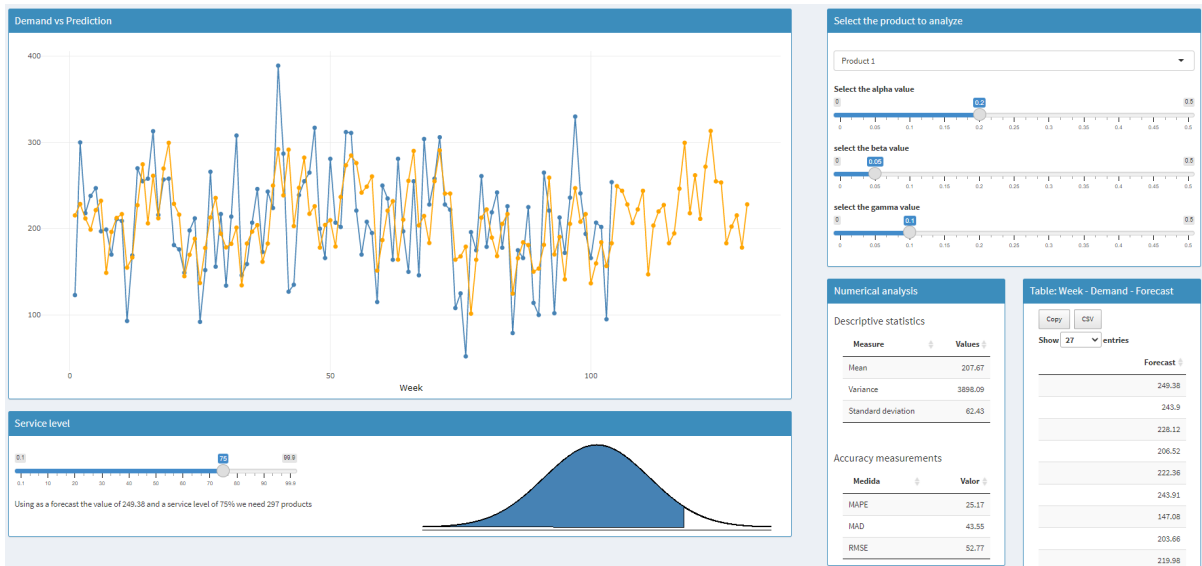
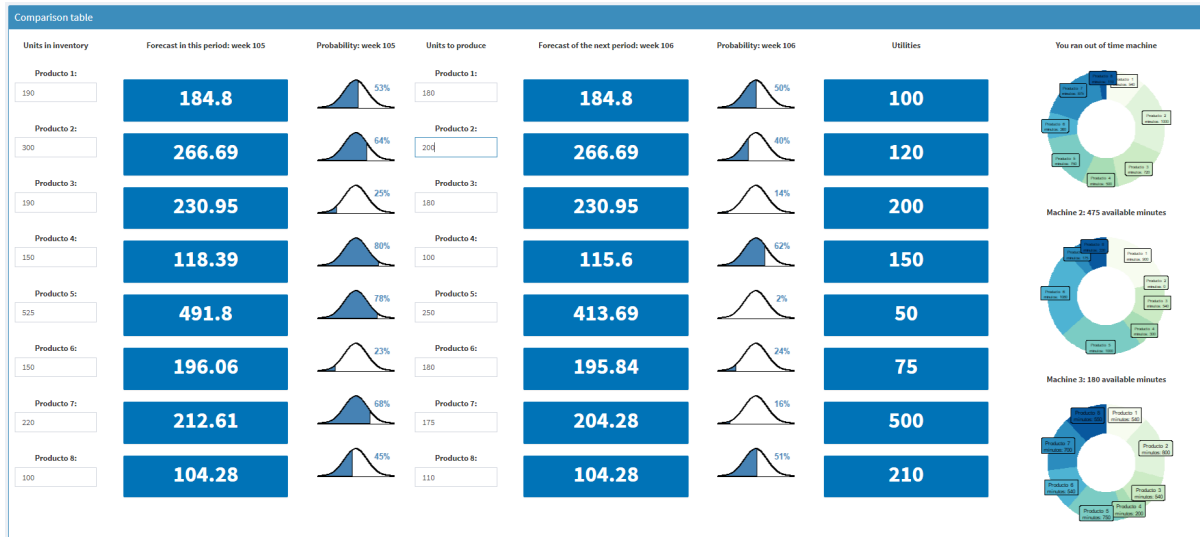


Figure 3: Structure of forecasting methods.

The last section of DHV can be seen in Figure 4, which works with two data sets, is presented. The first data set is obtained from the forecasting methods selected by the user. The second set of data comes from LOST and corresponds to the database of companies and suppliers.



**Figure 4:** Dashboard of final stage for decision making.

In this board the quantities of each product can be changed in real time, these values are used to calculate the predictions and the probabilities of satisfying the demand of the next period of the game. The donut graphs give information on the available machine time, and it has a minute counter. This board presents a summary of the variables of greatest interest so that the user can decide which product to select and the number of items to produce. Easy-to-interpret visualizations were chosen in pleasing-to-the-eye formats. Complex visualizations were not used since the data needed be presented in the simplest possible way. Traditional graphs and mixtures of them were taken into account, with components of colors and shapes that enhance the understanding of the data visualization.

#### 4. Methodology and Data Analysis

The experiment can be unfolded in two stages. In the first stage, the LOST simulator and the first version of the DHV are used. As a result of this first stage, adjustments and improvements were made to DHV. This first stage is qualitative research that intends to observe how the students used the DHV to make logistical decisions if the information and the graphics that the app provided were sufficient and presented in a proper way. Finally, it was intended to find the shortcomings of the app as a visual support for LOST. In this stage, interviews and perception surveys were carried out on students.

The second stage has a quantitative approach. LOST and the latest version of DHV are used. Variables related to the functionality, the processing and the interface of the tool are measured, as well as the decision-making of the students. Each stage is detailed below.

The first stage was used as a pilot, which helped defining the key parameters and the way in which various visualizations were going to be presented.

It is important to mention that our university carries out the implementation of a new academic plan that prevented the authors of this paper from having several groups of the same subject. Moreover, the length of the class was limited. Therefore, future work will include an out and an intra group design. The students of the first stage were registered in different periods, and in different subjects but with topics related to the game.

In order to avoid learning bias, one of the goals is to verify that students improved their results by using the tool and not by continuous use of the simulator.

##### 4.1 First stage – i-Week

The first stage of our experiment was depleted within the framework of the 2021 i-Week. The i-Week is an academic activity that is carried out nationally at Tecnológico de Monterrey. For an entire week the students carried out various activities such as seminars with experts from the industry, theoretical classes, practical workshops, among other activities. A group of 33 students had a one-week immersion to play LOST and to solve well-defined logistical challenges using DHV to support their decision making. During this period, a perception

survey was applied to the 33 students, who came from 5 campuses: Mexico City, Monterrey, Puebla, Querétaro and Toluca. The students were from different engineering fields from the last three semesters of their career. Random interviews were also conducted.

The survey had 9 items in the Likert scale ranging from 1 = Totally agree up to 7 = Totally disagree. The first two questions were related to the help provided by the visualization tools. The third and fourth questions referred to the opinion of the students about graphic resources. The fifth question dealt with the usability of the visualization tools. The sixth and seventh questions asked whether visualization tools helped them solve complex problems or not. The last two questions were related to the visualization support in decision making.

The Likert scale was especially useful in this experiment since a quantification of the student's opinion was required. In this sense, the response categories capture the intensity of the respondent's feelings towards a statement. There are studies that conclude that, from 8 levels, the results obtained are the same as with 9, so adding levels will not result in a greater variation in the results. Consequently, the optimum number of items lays within 7 or 8 levels (Joshi et al, 2015).

The survey was applied twice. The first time at the beginning of the week, after playing LOST. The second time was applied after showing them the visualization application DHV to be used when playing LOST again. Before starting the last game, they were taught how to use DHV. All the students attended a lecture on visualization and decision making.

#### **4.2 Second stage**

The second stage of the experiment was carried out in two groups of the Operation-Management subject aimed at fourth-semester-Industrial-Engineering students. The sample included 17 men and 19 women, that is 36 students in total.

The LOST game was introduced to the students, and they were asked to play the entire first level of the game. The students got the gist of the tool functionality by making logistical decisions, and by solving problems.

Once the first level was fully completed, a 15-item Pre-test was applied. It had three sections: Tool functionality (seven items), Data processing (two items) and User Interface (six items). The responses were presented on a Likert scale that ranged from 1 = Totally disagree up to 10 = Totally agree.

Subsequently, the students participated in a forecasting workshop for decision making and were introduced to the DHV app (version 2.0). Students learnt how to use DHV to analyze data for trends, seasonality, etc. They used DHV to make forecasts. Once this part was done, the students were ready to play LOST again. Depending on the decisions of the students, the game generated new routes, therefore, it was not the same game that they played before the Pre-test, but it had the same characteristics. At the end of the game, the Post-test was applied. The results are presented in the next section.

#### **4.3 Data Analysis**

##### *4.3.1 Stage one survey results*

To analyze the results of the seven-level-Likert-scale survey, new variables were created to represent each topic of interest. Concepts learning Q1+Q2, Graphic resources Q3+Q4, Usability of the tool Q5, Support offered to solve complex problems Q6+Q7 and Help in making decisions Q8+Q9. Table 2 shows descriptive statistics for these variables.

Likert scale data can be analyzed as interval data, i.e. the mean is the best measure of the central tendency. Here the average is used to calculate the functionality, the processing, and the interface gain.

On the other hand, after taking advantage of the Likert scale so that the student can differentiate the degree of agreement with the statement, a breakdown of the data into three intervals was used, through the mean and the deviation, imitating the analysis of data with normal distribution.

**Table 2:** Descriptive statistics of the new variables.

Variable	N	Minimum	Maximun	Mean	Std. Deviation
Concepts LOST Q1+Q2	33	2.00	14.00	5.5758	4.02360
Concepts DHV Q1+Q2	33	2.00	13.00	5.0909	3.80266
GraphResources LOST Q3+Q4	33	2.00	12.00	5.7879	2.83678
GraphResources DHV Q3+Q4	33	2.00	14.00	5.4242	3.78344
Usability LOST Q5	33	1.00	7.00	4.0909	1.75648
Usability DHV Q5	33	1.00	7.00	2.7273	1.87538
CoplexTask DHV Q6+Q7	33	2.00	14.00	5.3030	3.79543
CoplexTask DHV Q6+Q7	33	2.00	14.00	6.6061	3.41814
DesicionMaker LOST Q8+Q9	33	2.00	14.00	6.3333	3.67140
DesicionMaker DHV Q8+Q9	33	2.00	14.00	5.5152	3.80067

To facilitate the study, the bins using the cutoff points obtained are found as follows:  $\mu \pm 0.75\sigma$

where  $\mu$  is the mean and  $\sigma$  represents the standard deviation of the variable. The student percentage whose opinion falls into the three ranges was taken into account as:

$$[minimum, \mu - 0.75\sigma), [\mu - 0.75\sigma + 0.75\sigma], (\mu + 0.75\sigma, maximum]$$

Table 3 shows the percentage of students in each range on the topics impacted by the LOST and the DHV tools. It was found that 69.7% of the students perceived that LOST helped them to learn the concepts, while 36.4% of the students perceived that DHV as an additional aid to learning the concepts. These percentages increased when considering the intermediate ones, this is: 78% and 76% respectively. 42.4% of the students thought that the graphic resources presented by the two tools were good. If we add the intermediate ones, it would be 81% in both tools. 36.4% of the sample said that LOST was easy to use, while 30.3% consider that the tool helps in solving the tasks carried out.

**Table 3:** Percentage of students in each range on the topics impacted by the LOST and DHV tools.

Questions	Topics	LOST			DHV		
		High	Intermediate	Weak	High	Intermediate	Week
Q1-Q2	Learning Concepts	69.7%	9.1%	21.2%	36.4%	39.4%	24.2%
Q3-Q4	Graph Resources	42.4%	39.4%	18.2%	42.4%	39.4%	18.2%
Q5	Usability	36.4%	36.4%	27.3%	30.3%	48.5%	21.2%
Q6-Q7	Solve Task	30.3%	45.5%	24.2%	30.3%	51.5%	18.2%
Q8-Q9	Decision Maker	42.4%	36.4%	21.2%	36.4%	45.5%	18.2%

#### 4.3.2 Stage two: survey results

The 15-item questionnaire was studied through three variables: tool functionality (Functionality), data processing (Processing) and user interface (Interface). They were obtained with the average of the corresponding questions and continuous values between 1 and 10 were obtained.

Seven questions are related to the functionality of the tool, these questions deal with the visualization and its relationship with decision making. A high score on "Functionality" indicates that the student believes that the way the tool displays the resources such as the tables, the data, and the graphs facilitates the decision making. Two questions are related to data processing. A high score in "Processing" indicates that the student considers that the tool has what it takes to be able to manipulate, to process and to represent the results. Six questions relate to the user interface. A high score on "Interface" indicates that the student is comfortable with colours, the way the information is presented, and the visualization layout.

**Table 4:** Statistics on Functionality, Processing and Interface.

Variable	Functionality		Processing		Interface	
	Pre	Post	Pre	Post	Pre	Post
Mean	9.004	9.405	6.708	8.167	8.222	9.009
StDev	0.838	0.662	1.857	1.608	0.987	0.921

To proceed with the data analysis, the following variables (Hake 1998; Loza et al, 2022) were used. Average pre-test grade:

$$\langle Pre \rangle = \frac{1}{N} \sum_{i=1}^N (Pre_i)$$

where  $(Pre_i)$  is the pre-test grade of the student  $i$ ; and the average post-test grade:

$$\langle Post \rangle = \frac{1}{N} \sum_{i=1}^N (Post_i)$$

where  $(Post_i)$  is the post-test grade of the student  $i$ .  $N = 33$  is the sample size.

Student Functionality/ Processing /Interface gain:

$$G_i = \langle Post_i \rangle - \langle Pre_i \rangle$$

Group Functionality/Processing/Interface gain:

$$G = \langle Post \rangle - \langle Pre \rangle$$

Student relative Functionality/Processing /Interface gain:

$$g_i = \frac{Post_i - Pre_i}{10 - Pre_i}$$

The relative Functionality/Processing /Interface gain for a given student is a measure of the actual gain that the students achieved, i.e.,  $Post_i - Pre_i$  with respect to the maximum gain that they could have obtained  $10 - Pre_i$ . The group relative Functionality/Processing /Interface gain has a similar meaning but refers to the whole group:

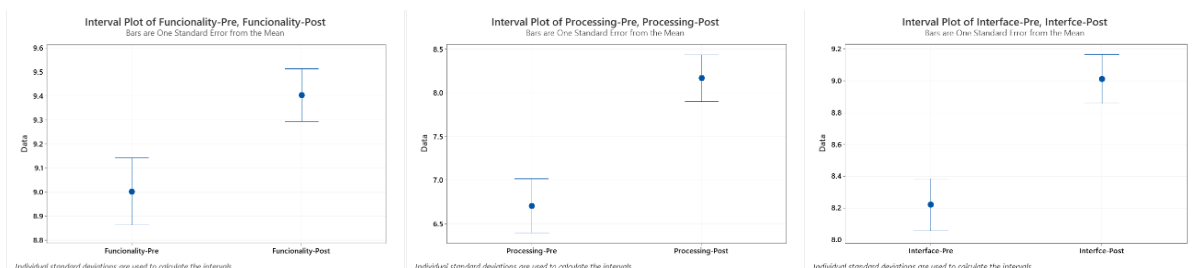
$$g = \frac{\langle Post \rangle - \langle Pre \rangle}{10 - \langle Pre \rangle} = \frac{G}{10 - \langle Pre \rangle}$$

**Table 5:** Gain in Functionality, Processing, and Interface.

	Pre	Post	G = Post - Pre	g = G / 10 - Pre
<b>Tool functionality</b>	9.00	9.40	0.40	0.40
<b>Data processing</b>	6.71	8.17	1.46	0.44
<b>User interface</b>	8.22	9.01	0.79	0.44

Table 5 shows a gain in functionality of 40% and 44% in processing and interface. This means that by playing LOST with the support of DHV, students perceive that there is an improvement in visualization, which leads to better data analysis and decision making in a comfortable design environment.

Figure 5 shows the graph of functionality, processing, and interface, where is observed that the results post-test are significantly higher than the pre-test.



**Figure 5:** Interval plot for Functionality, Processing, and Interface.

## 5. Conclusions

The app Data Hound and Visualizations (DHV) is designed to guide users in their decision-making process. To perform this task, the tool focuses on three key aspects: functionality, processing, and interface. The obtained results indicate that LOST and DHV help the users to better understand the problem, to analyze it and to solve it. Large amounts of data complicate the decision making, so the use of a tool capable of processing large data sets, presenting the data sets as tables, graphs and interactive dashboards, besides performing calculations in

real time, relieves the user of various complex tasks. With the help of DHV, the user can focus on the understanding and on the analysis of the scenarios proposed in the LOST game. DHV is scalable to new and diverse versions of the game, it is even possible to adapt it for environments other than LOST.

This paper contributes to underline the importance of visualization in student learning, considering that currently big data, industry 4.0, internet of things have gained relevance in our modern world. Not only is it necessary the design of strategic games involving these new variables, but it is imperative to keep in mind that the more complex a system, the greater the number of visualization tools required to strengthen the comprehension of the system and the student learning.

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