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Support Systems for Decision Makers: Impact on Performance

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***Abstract*—This study examines several decision process factors and their impact on company performance. It addresses this problem via Decision Support Systems (DSS). Data extracted from a simulation exercise with 794 senior graduate students who developed DSS informs this investigation. Our analysis shows that the perceived usefulness of the system correlates to improved company performance, as does the level of user satisfaction with the system. Last, the study exemplifies how different systemic decision traits can impact system perceived usefulness, user satisfaction, ease of use, and familiarity with the system.**

***Index Terms*—Decision Making, System Use, Simulation, Performance.**

I. INTRODUCTION

Decision Support Systems (DSS) are ubiquitous in providing computer-based support for decision makers charged with solving semi-structured and unstructured problems. Studies show that DSS are effective if the users' systemic design objectives or performance expectations are achieved [16]. This is because the information needs of the users (the decision makers) are appropriately supported by the system [19]. Studying human behavior is, thus, key [28]. Users today are more involved in the system's development process, as they will eventually use the tool [14]. Therefore, it is vital to better understand the relationship between certain decision variables and their impact on both organizational and decision performance [7].

Several studies explain that the organizational and external environments of decision systems are key determinants in the success or failure of those systems (e.g., [1]). Environmental factors are usually fluid, dynamic, and difficult to control, thus they invariably distort the meaning of data collected in trans-organizational DSS comparisons. This study, therefore, employs a simulation platform in a controlled setting. The simulation functions as the platform for participants to experience decision making scenarios. We use the simulation as a tool for measuring several decision process variables. Our objective is to measure the perceived benefits of DSS, so we administer a questionnaire on their use, user satisfaction and performance.

This research follows an approach akin to [3] who considered DSS simulations and their educational efficacy. We augment that investigation by shifting the focus to the systems, the users, and the impact on performance. Classes of students formed groups and participated in a simulation exercise. The groups, simulating companies in an industry, developed DSS that were later characterized and analyzed. In addition, several variables related to DSS perceived effectiveness were evaluated and compared to group performance.

The remainder of the paper is organized as follows. First, we review relevant literature, present our theoretical model and set the study's hypotheses. Then, we describe the employed methodology (the simulation). Next, we examine the implementation of DSS in the proposed simulation and analyze related variables. Finally, we discuss the applicability of this study and draw conclusions.

II. LITERATURE REVIEW AND HYPOTHESES

Relatively few studies integrate decision process variables, such as perceived usefulness, satisfaction, perceived ease of use and familiarity (see, for example, [17], [27]).

The lack of studies that incorporate decision process variables may be relate to a perception that such variables are less important and more generic; thus, challenging to capture or measure [16]. Moreover, many studies argue that DSS serve the sole purpose of goal attainment (for example, performance). As a result, researchers' attention is usually focused on that goal and the ways in which to reach it. This practice diverts attention from decision process variables ([20], [23]).

Nevertheless, as economic environments grow increasingly complex, DSS function as an integral element of the workplace and they are used to make strategic decisions, not just to optimize or solve simple work problems [16]. This underscores the importance of understanding how behavioral and cognitive decision factors impact economic decision and performance.

Figure 1 illustrates the research model. The model shows that the impact of DSS use on decision outcomes (i.e., performance) is mediated by these decision process variables: (1) perceived usefulness; (2) perceived ease of use; (3) user satisfaction; and (4) perceived familiarity. Moreover, DSS use moderates the (negative) impact of system complexity on several decision process variables. Finally, we hypothesize that the relationship between system complexity and perceived usefulness and user satisfaction is represented

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by nonlinear, inverted U-shaped curve. We articulate this below.

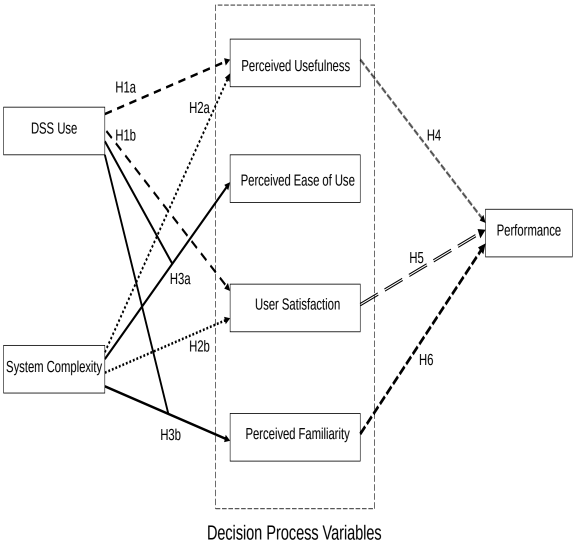

Fig 1. The Research Model

Several studies indicate that information systems facilitate a reduction in complexity when a good fit is created between the task, necessary information, and how the problem represents itself. This factor renders decision-making processes more efficient and significantly faster ([14], [15]). Therefore, given the complexity of information processing required in a business environment, we expect that our subjects will prefer the combination of a sufficiently robust DSS technology and a sufficiently intuitive DSS interface.

The use of DSS may reduce information complexity, thus, increasing perceived usefulness of the system. Perceived usefulness is defined by [5] as the degree to which users perceive a particular system as enhancing their performance. Literature shows that DSS use can increase perceived usefulness (see, for example, [27]). Therefore,

H1a: DSS use is positively related to perceived usefulness.

DSS use can also have a positive impact on various perceptions, such as user satisfaction. User satisfaction is a process variable that is referred to in research as a measure of the individual experience [3]. User satisfaction is defined as the inherent satisfaction with the interaction with DSS. Various researchers examined the fit between tasks, which determine challenges for users, and technology (for example, DSS), which can restrict or extend the users' information processing skills. Studies show that user satisfaction can be increased if a good fit is created between the technology interface and the task [4]. Thus,

H1b: DSS use is positively related to user satisfaction.

We also hypothesize that as system complexity increases, perceived usefulness and user satisfaction also improve, provided that the user remains confident in the system's ability to solve problems, and that he or she finds the system intuitive. But only to a point. As the complexity increases beyond a certain degree, perceived usefulness and user satisfaction stop increasing and start declining – following an inverted U-shaped curve. System complexity can be measured by the choice set size, the use of analytic tools or information presentation format [16].

When the system is simple, users enjoy operational command of the system. With this command, they are exposed to a decision construct, one where the user may be satisfied even in the selection of the less-than-optimal choice [26]. Simultaneously, the users know that the decisions could have been made without the system, fueling a perception the system as relevant to the task, but not essential [16]. In this context, user satisfaction and perceived usefulness are low.

As the system's level of complexity increases, users start to be constrained by their cognitive limitations [26] and the role of the DSS becomes more vital, i.e., a fit between the tasks at hand and the system is created [12]. Studies show that users employ DSS to increase the depth and breadth of factors that impact a given decision, improving their decision-making efficiency and helping them make more informed decisions. This also yields higher levels of decision satisfaction with the outcome, even though the level of complexity increases ([26], [27]). As users increasingly use DSS in decision making, perceived system's usefulness increases as well.

As complexity increases beyond a threshold, the system reaches its useful limit. Users become overwhelmed [16]. And although users may still perceive the DSS as essential, their satisfaction and perceived usefulness are reduced. More specially, dissatisfaction emerges when users question if they have maximized system's potential. Thus, complexity strongly correlates to user satisfaction and perceived usefulness.

To summarize, our hypothesis is that as system complexity increases, both perceived usefulness and user satisfaction also increase. However, as the complexity increases beyond a certain point, both perceived usefulness and user satisfaction stop increasing and start to decline, following an inverted U-shaped curve. Thus,

H2a: Perceived usefulness follows an inverted U-shaped curve as system complexity increases.

H2b: User satisfaction follows an inverted U-shaped curve as system complexity increases.

Studies show that increases in system complexity cause decrease in ease of use perceptions by users. Also important, that the appropriate fit between the tasks at hand and the system can increase user perceptions of

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ease of use. Therefore, we hypothesize that DSS use can moderate the negative effects of increasing system complexity on perceived ease of use. Thus,

H3a: The negative effects of increasing system complexity on perceived ease of use are alleviated by the use of the system.

Understanding perceived familiarity is useful to the extent that it reveals users' level of familiarity with the system. It also exhibits the level of control, frustration and confusion that users experience when interacting with the system.

We hypothesize that system complexity will negatively impact perceived familiarly, but as with ease of use, this effect is alleviated by DSS use. Our basis is on research in decision-making that shows increasing system complexity may increase mental overload fretfulness beyond the decision maker's competency. As a result, the decision maker is unable to analyze and process all available information, leading to feelings of anxiety [26]. However, literature has also shown that this frustration and confusion can be eased by employing technology (e.g., DSS), and thus, complement the decision maker's information processing competencies (see, for example, [4], [26]). Therefore,

H3b: The negative effects of increasing system complexity on perceived familiarity are alleviated by the use of the system.

The DSS literature is replete with studies addressing the direct effects of DSS use on decision outcomes (e.g., [2], [8], [19]). It was not until more recently that research introduced the mediating effects of the decision process between DSS use and decision outcomes ([16], [17]). We gleaned valuable insights from these studies that explored the subjective measures of decision outcomes, like user behavior or intentions (see, for example, [13], [16], [19]). However, our point of departure is the introduction of an objective measure of performance on the belief that it more appropriately expresses economic outcomes.

Our discussion on the above hypotheses reinforces our expectation that DSS use has a direct impact on decision-making processes. Studies have shown that the variables used in this study to represent the decision process directly impact performance: [18] investigated user satisfaction; [5] examined perceived usefulness; and [3] studied perceived familiarity. Given this corpus of verification, we believe that the decision process variables will mediate the impact of DSS use on performance. That is,

H4: Perceived usefulness will mediate the effect of DSS use on performance.

H5: User satisfaction will mediate the effect of DSS use on performance.

H6: Perceived familiarity will mediate the effect of DSS use on performance.

We do not anticipate that perceived ease of use will present any effect as [5] showed that it indirectly affects performance through perceived usefulness. Thus, we do not assume a direct impact.

III. METHODOLOGY: THE SIMULATION EMPLOYED

A simulation is a highly complex man-made environment, which provides participants the opportunity to "learn by doing" in as authentic a situation as possible. It also engages them in a simulated experience of the real world (e.g., [10], [21]). This usually enhances the characteristics of the simulation to mirror real life behavior.

The use of simulations in studying systems is well documented in the literature. For example, [9] used a simulation to explore Enterprise Resource Planning concepts. An Internet-mediated simulating an electronic commerce environment was investigated by [22]; a simulation in technology management settings is described by [3] and [4].

This study employs the International Operations Simulation: INTOPIA B2B (http://www.intopiainc.com). This simulation represents a tool that successfully enables participants to develop analytical decision making skills, including problem identification skills, data handling skills, and critical thinking skills. Moreover, the improvement of technology and the development of web applications render simulation exercises more sophisticated and user friendly in the past decade [3]. We use the simulation to establish a managerial decision-making context: The simulation involves participants in the executive process, requires them to develop decision-making aids (systems), and forces them to adopt an executive viewpoint associated with DSS.

The study was conducted in a university accredited by the Association to Advance Collegiate Schools of Business (AACSB). The participants were senior graduate students. The students were divided into 4 or 5-participant-teams (simulating companies in the industry) and immersed themselves in an artificially created hi-tech industry, where companies conducted research, and produced and marketed computer chips and PCs. The teams were created without external intervention or manipulation from the researchers. Each team operated in simulated markets similar to the markets in the United States (US), the European Union (EU) and Brazil. "Operating" is a broad concept that covers any one or any combination of the manufacturing, marketing, distributing, exporting, importing, financing and licensing functions.

We conducted ten runs of the simulation with different participants in each run: (1) Run I, with 20 teams; (2) Run II, with 20 teams; (3) Run III, with 18

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teams; (4) Run IV, with 16 teams; (5) Run V, with 15 teams; (6) Run VI, with 20 teams; (7) Run VII, with 15 teams; (8) Run VIII, with 20 teams; (9) Run IX, with 21 teams; and (10) Run X, with 13 teams. Each run of the simulation was conducted for a full semester. Participants played six simulated periods (each representing one year). Companies were instructed to make decisions which would guide operations (simulated by a relatively easy computer interface) in the forthcoming period and which would also affect operations in subsequent periods. In each run, decisions were made once a week and were e-mailed to the instructor to be fed to the computer program. After the program ran the data, it generated company outputs that included financial reports (e.g., a balance sheet, an income statement), production reports and market researches. After the system generated outputs, they were e-mailed to the teams and were used for decision making in sequential periods. Dozens of decisions, typical of standard businesses, were required of a company in each period. The decision-making process was based on an analysis of the company's history, interaction with other companies, and the constraints articulated in the simulation manual (e.g., procedures for production, types of available marketing channels).

Success in the simulation was measured by company performance. Following [11], we measured company performance by its accumulated net profits. Net profit was affected by the company's decisions, simulated customer behavior, and the competition – the other companies in the industry.

As each run commenced, a requirement to develop and report on DSS was communicated to the participants. It is important to note that the participants themselves, without any intervention from the researchers, had to determine who would develop the system and what type of system it would be. At the end of each run, after the last set of decisions had been made, each group was required to present its system in class and a corresponding report. At that same meeting, each student completed a short individual questionnaire on the DSS assignment (see Table I for the text of the questionnaire). Seven hundred ninety-four participants completed the questionnaire.

TABLE I. THE QUESTIONNAIRE

		Strongly Disagree	Disagree	Tend to disagree	Neutral	Tend to agree	Agree	Strongly agree
1.	I am familiar with the system developed in the company	1	2	3	4	5	6	7
2.	The system is useful for decision making	1	2	3	4	5	6	7
3.	The system was easy to use	1	2	3	4	5	6	7
4.	I am satisfied with the system	1	2	3	4	5	6	7
5.	I used the system for making decisions	1	2	3	4	5	6	7

IV. RESEARCH FINDINGS

A. Developed Systems

Approximately 60% of the companies in every run nominated a Chief Information Officer (CIO). All companies reported developing an information system, yet none of the companies reported major modifications during the run. We present an example of the systems developed in Run I. Twenty companies were created in that run, most of which developed a Microsoft Excel spreadsheet-based DSS. Table II illustrates the major characteristics of the systems developed.

For our purpose, the most relevant aspect of Table II is the extent to which the companies differed on their systems. Each company adopted its own application areas with models including statistical analyses, spreadsheets, and even linear regressions. Only 9 companies (5% of total) utilized package software (most used 'Easy Plan'). One hundred and nineteen companies developed complicated data analysis tools (mostly statistical or engineering analyses) for their systems (67% of total). Only 65 companies developed graphic outputs (about 37% of total), while the remaining 113 companies did not. Finally, the sophistication and complexity of the models employed varied significantly from simple spreadsheet analyses (companies 1, 16 and 18 in Run I) to complex linear models (company 11 in that same run). While it cannot be claimed that the distribution of attributes of systems exactly measures that in the real world, the degree of diversity of systems developed, based on existing tools, does appear to be quite real.

In the following, we test the study's hypotheses by examining decision process variables and company performance. The latter is analyzed with respect to the developed DSS. Table III lists means and standard deviations of responses to the five questions.

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TABLE II. CHARACTERISTICS OF SYSTEMS DEVELOPED BY COMPANIES IN RUN I.

Co.	System Area	Nature of System	Data Analysis	Graphics
1	Production, Finance	Electronic Sheet	No	No
2	Production, Finance, Market Analysis	Electronic Sheet	Yes	No
3	Production, Finance, Market Analysis	Electronic Sheet	Yes	No
4	R&D, Production, Finance, Marketing, Market Analysis	Electronic Sheet	Yes	No
5	R&D, Production, Finance, Marketing	Electronic Sheet	No	Yes
6	R&D, Production, Finance, Marketing, Market Analysis	Electronic Sheet	Yes	No
7	Production, Finance	Electronic Sheet	Yes	No
8	Production, Finance	Electronic Sheet	Yes	Yes
9	R&D, Production, Finance, Marketing	Electronic Sheet	No	No
10	Production, Finance, Marketing	Electronic Sheet	No	No
11	R&D, Production, Finance, Marketing, Market Analysis	Electronic Sheet, Regressions	Yes	Yes
12	R&D, Production, Finance, Market Analysis	Electronic Sheet, Regressions	Yes	No
13	R&D, Production, Finance	Electronic Sheet	No	Yes
14	Marketing, Market Analysis	Electronic Sheet, Regressions	Yes	No
15	Finance, Marketing, Market Analysis	Electronic Sheet	Yes	Yes
16	Finance, Marketing	Electronic Sheet	No	No
17	Finance, Marketing, Market Analysis	Electronic Sheet	Yes	Yes
18	Production, Finance	Electronic Sheet	No	No
19	Production, Finance	Easy Plan, Electronic Sheet	No	No
20	Production, Marketing	Electronic Sheet	Yes	Yes

TABLE III.
MEANS AND STANDARD DEVIATIONS (S.D.) OF RESPONSES.

Variable	n=794	
	Mean	S.D.
Familiarity	5.33	0.87
Usefulness	5.72	0.83
Ease of Use	5.80	0.85
User satisfaction	5.69	0.85
Use	5.68	0.81

B. DSS Use and System Complexity vs. Perceived Usefulness and User Satisfaction (Hypotheses H1a, H1b, H2a and H2b)

In this section we examine the impact of system use and system complexity on the following two decision process variables (Hypotheses H1a, H1b, H2a and H2b):

1. Usefulness of the system as evaluated by participants (question 2)
2. User satisfaction (question 4).

We conducted a partial least squares (PLS) analysis. The results for hypotheses H1a and H1b are presented in Table IV. Overall, the two coefficients are positive and the results are significant: This supports H1a and H1b.

TABLE IV. RESULTS FOR PERCEIVED USEFULNESS AND USER SATISFACTION (H1A AND H1B): COEFFICIENTS, T-STATISTIC AND P-VALUE; N=794

Variable	Coefficient	t-stat	p-value
Perceived Usefulness	0.0874	2.4171	0.0158
User Satisfaction	0.1180	3.1813	< 0.01

Next we test the hypotheses on the nonlinear, inverted U-shaped relationships between system complexity and DSS perceived usefulness and user satisfaction (Hypotheses H2a and H2b). To measure the level of complexity, we followed classifications of previous studies (e.g., [3]) and organized the developed systems from all runs in three categories according to: (1) the number of functional areas they cover (e.g., production, finance, R&D, marketing); and (2) their use of graphics and data analysis tools. The three levels of complexity were as follows:

(a) Plain complexity – systems that did not use graphics or any data analysis tools. For example, in Table I, companies 1, 9, 10, 16, 18 and 19 developed systems with plain complexity.

(b) Moderate complexity – systems that employed either graphics or data analysis tools (or both) and covered up to three functional areas. For example, in Table I, companies 2, 3, 7, 8, 13, 14, 15, 17 and 20 developed systems with moderate complexity.

(c) Multifaceted complexity – Systems that employed either graphics or data analysis tools (or both) and covered more than three functional areas. For example, in Table I, companies 4, 5, 6, 11 and 12 developed systems with multifaceted complexity.

Then, we matched the companies' data with the corresponding level of system complexity. The results are illustrated in Figure 2. It seems that companies with plain system complexity expressed the lowest levels of perceived usefulness and user satisfaction while companies with moderate system complexity expressed

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the highest levels of perceived usefulness and user satisfaction. The graph presents an inverted U-shaped relationship between system complexity and the two measured variables.

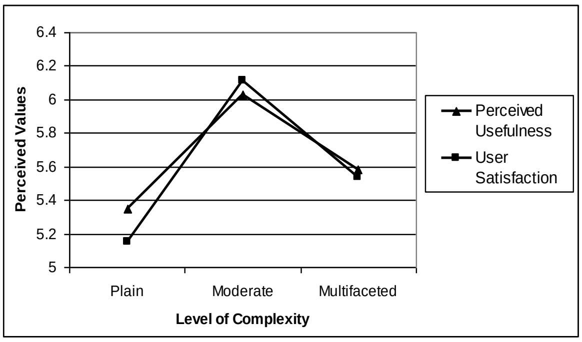

Fig 2. Means of perceived usefulness and user satisfaction for different levels of system complexity.

To strengthen our analysis of those relationships, we arranged two dummy variables, C1 and C2, to form the nonlinear relationships, as follows (PLS is restricted to linear relationships only and therefore, a direct measurement of nonlinear relationships is irrelevant):

Plain complexity; C1=0; C2=0

Moderate complexity; C1=1; C2=0

Multifaceted complexity; C1=1; C2=1

Next, we examined the coefficients for the relationships of C1 and C2 with perceived usefulness and user satisfaction. We note that a significant positive coefficient for C1 would indicate that perceived usefulness and user satisfaction increase when system complexity increases from 'plain complexity' to 'moderate complexity'. A significant negative coefficient for C2 would indicate that perceived usefulness and user satisfaction decrease when system complexity increases from 'moderate complexity' to 'multifaceted complexity'. The results, presented in Table V, support those notions: The coefficients between the dummy variables C1 and C2 with perceived usefulness and user satisfaction are as expected: C1's coefficients are positive and significant and C2's coefficients are negative and significant. Therefore, hypotheses H2a and H2b are supported.

TABLE V. RESULTS FOR C1 AND C2 (H2a AND H2b): COEFFICIENTS, t-STATISTIC AND p-VALUE; n=794

	Variable					
	Perceived Usefulness			User Satisfaction		
Variable	Coefficient	t-stat	p-value	Coefficient	t-stat	p-value
C1	0.6242	10.7885	< 0.01	0.8054	14.2597	< 0.01
C2	-0.1634	-1.9777	0.0483	-0.1733	-2.0696	0.0388

C. DSS Use and System Complexity vs. Perceived Ease of Use and Perceived Familiarity (Hypotheses H3a and H3b)

In this section we examine the moderating effects of system use on the relationship between system complexity and the following two decision process variables (Hypotheses H3a and H3b):

1. Perceived ease of use (Question 3)
2. Perceives familiarity (Question 1)

To test the hypotheses, we examine the coefficients between system complexity and perceived ease of use and perceived familiarity. Again, we use the two dummy variables, C1 and C2, as system complexity is a categorized variable. Note that significant negative coefficients for both C1 and C2 relative to both perceived ease of use and perceived familiarity suggest that ease of use and perceived familiarity decrease when system complexity increases.

The results below support this notion: Table VI reveals the coefficients between the dummy variables C1 and C2 with perceived ease of use and perceived familiarity are as expected: C1's and C2's coefficients are negative and significant. Those results verify the negative relationship between system complexity and the two process variables.

To examine the moderating effect of DSS use, we created two interaction terms: DSS use *times* C1 (hereafter, USEXC1) and DSS *times* C2 (hereafter, USEXC2). Positive coefficient between those two terms and the two process variables would indicate that DSS use positively impacts them. The results support this statement, as each term is positive for both process variables: USEXC1's and USEXC2's coefficients are positive and significant (see Table VI). Those results indicate that DSS use positively moderates the negative relationship between system complexity with perceived ease of use and perceived familiarity. Thus, we were able to confirm H3a and H3b.

TABLE VI. RESULTS FOR C1, C2, USEXC1 AND USEXC2 (H3a AND H3b): COEFFICIENTS, t-STATISTIC AND p-VALUE; n=794

	Variable					
	Perceived Ease of Use			Perceived Familiarity		
Variable	Coefficient	t-stat	p-value	Coefficient	t-stat	p-value
C1	-0.1647	-2.5977	< 0.01	-0.1535	-2.3703	0.0180
C2	-0.1798	-2.0003	0.0458	-0.1849	-2.0238	0.0433
USEXC1	0.0256	2.3806	0.0175	0.0229	2.0811	0.0377
USEXC2	0.0294	1.9695	0.0492	0.0324	2.0658	0.0392

D. Company Performance Analysis (Hypotheses H4, H5 and H6)

This section investigates the mediating role of the process variables between DSS use and company performance (H4, H5 and H6). As noted above,

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performance was measured by the companies' accumulated net profit. To correctly compare results between runs, we express the net profit in terms relative to the average company in each run. Comparing absolute values may create a bias, as the industries evolved differently and a company that performed poorly in one run, i.e., did not produce a lot of profit, could be considered an average company in another run, where all companies competed fiercely and did not produce significant profits. Table VII presents an example of company performance in Run IV, including absolute and relative values.

TABLE VII. PERFORMANCE (NET PROFIT) OF COMPANIES IN RUN IV EXPRESSED IN ABSOLUTE AND RELATIVE VALUES.

Company No.	Net Profit ($)	Relative Net Profit (%)
1	21,315	-5.3
2	18,169	-19.2
3	45,423	101.9
4	826	-96.3
5	19,957	-11.3
6	36,945	64.2
7	21,458	-4.6
8	34,363	52.7
9	16,665	-25.9
10	20,301	-9.8
11	16,543	-26.5
12	27,571	22.5
13	12,342	-45.1
14	23,892	6.2
15	25,206	12.0
16	19,016	-15.5
Average	22,500	0.0

The non-significant direct relationship between DSS use and company performance ($\beta = 1.3417$, p-value = 0.1958; also see Table VIII) indicates that the effect of DSS use on company performance may be indirect. This is verified by two process variables: perceived usefulness and user satisfaction. As shown above and in Table IV, the effect of DSS use on both those variables is positive and significant ($\beta = 0.0874$, p-value = 0.0158 for perceived usefulness and $\beta = 0.1180$, p-value < 0.01 for user satisfaction). In addition, the effect of both perceived usefulness and user satisfaction on company performance is also positive and significant (see Table VIII). Perceived familiarity, however, does not present a significant effect on company performance (also see Table VIII). Therefore, hypotheses H4 and H5 are supported, while H6 is not.

TABLE VIII. RESULTS FOR DSS USE, PERCEIVED USEFULNESS, USER SATISFACTION AND PERCEIVED FAMILIARITY (H4, H5 AND H6): COEFFICIENTS, t-STATISTIC AND p-VALUE; n=794

Variable	Coefficient	t-stat	p-value
DSS Use	1.3417	1.3287	0.1958
Perceived Usefulness	6.0919	5.0642	< 0.01
User Satisfaction	7.0825	6.0237	< 0.01
Perceived Familiarity	0.1210	0.1448	0.8862

IV. DISCUSSION

This study examined simulated companies. Although the general environment that each team functioned within was similar, the companies became differentiated. And leaving system development decisions to the companies resulted in a variety of applications and a wide array of models, programs and modes of operation. It appears that these companies reflect most real life business approaches to DSS.

Moreover, although participants were not instructed to develop particular types of DSS, most companies developed spreadsheet-based systems. Some may regard spreadsheets as over simplistic systems. However, spreadsheet technology is considered robust and reasonably understandable for building model-driven DSS in an end user development environment or in a multi-user environment [25]. Spreadsheet-based DSS today have become the most ubiquitous DSS generators as they have sophisticated data handling, graphic capabilities and they can be used for "what if" analysis purposes (for more examples of decision systems, see [24]).

Furthermore, spreadsheets-based systems offer some substantial advantages: individuals, not necessarily information systems oriented, are usually familiar with spreadsheet tools, so they can quickly employ them for the development of DSS. Spreadsheets also allow a dynamic data updating and facilitate data visualization. Also, modern spreadsheet programs contain powerful data analysis tools (e.g., Analysis ToolPak, Crystal Ball and Solver in Excel); more than 60% of all participating teams incorporated those data analysis tools into their systems.

Overall, those analysis tools and the resulting systems were based on real-world decision systems. For example, the use of precision trees to determine operation activities in the different (simulated) markets (US, EU and Brazil) was based on Proctor and Gamble's use of this spreadsheet add-in to make decisions on site locations [25]; assessing financial risks was based on DSS tools developed by Decisioneering, Inc for assessing the risk of commercial loans [6].

This study also tested six hypotheses; five were confirmed: The first hypothesis, relating system use to perceived usefulness and user satisfaction was confirmed. The second hypothesis was also confirmed, as perceived usefulness and user satisfaction follow an inverted U-shaped curve as system complexity increases. The third hypothesis was confirmed too, as system use positively moderates the negative relationship between system complexity and perceived ease of use and perceived familiarity. The last three hypotheses tested the mediating effect of three decision variables on performance. While two variables, perceived usefulness and user satisfaction, were

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confirmed to mediate the effect of system use on performance, perceived familiarity was not. These results replicate a number of previous findings.

More generally, our experience suggests that the efficacy of simulations as platforms for implementing DSS is twofold. First, participants practice the art of decision-making; participants are excited, motivated and strive to make better decisions; they become actively involved in the simulated decision-making process and in the development of systems of their choice. Second, because the simulation is very practical, the participants themselves frame the relationship between the decision-making processes, the designed information systems and the outcomes of their use. This exemplifies how decision-making is more effective using DSS and also provides an integrative view of some of the tasks and practical uses of DSS.

V. CONCLUSIONS

The results of this work have implications for both researchers and practitioners. For researchers, this study demonstrates the importance of including perceived decision measures when examining decision making and system effectiveness. Nevertheless, researchers should exercise cautious when selecting measures of system usefulness and company performance. While some measures are positively associated with system usefulness or company performance, other factors do not present a direct impact. In addition, researchers should clearly specify what the exact nature of the measured variables is. As this study proved, system use and system usefulness may produce entirely different user effects.

The implications for practitioners are also important. First, we have shown a nonlinear, inverted U-shaped relationship between complexity and two of the decision process variables, signifying that multifaceted systems do not guarantee a better outcome. Therefore, as perceived effectiveness becomes increasingly important, more and more businesses should concentrate on that aspect of their systems. And this work shows how to seamlessly shift the study of DSS from theoretical concepts and research aspects to more practical and relevant contexts. That is, the simulation encourages participants to apply scientific concepts and to create a system that supports problem solving activities using the available data. The ultimate result will be more effective decision making systems in the real world.

Second, practitioners need to realize that a lack of strong behavioral indications of system familiarity or system use may not necessarily result in a negative outcome. In fact, as this study showed, there may very well exist other factors that impact performance. By better understanding the perceived measures of system effectiveness and company performance, practitioners could interpret data pertaining to those measures more accurately. System analysts and system developers should heed this result while developing or designing systems and involving the decision makers in the process.

Furthermore, since the simulation decisions are more simplistic than those of the real world, the systems required to support these decisions are less robust than systems in reality. Therefore, the generality and the application of the findings should be further explored by subsequent research. In addition, there is a need to determine how the type of systems developed in this study capture the complexity and the dynamic aspects of real systems in the industry. That is, future research should explore how the systems developed in this study reflect real-life applications of support systems.

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