Decision-Support Systems and Decision Making: Managing Decisional Deskilling in Human-DSS Interactions in Organizations

A Quantitative Study

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***Abstract*—The loss of individual decision-making skills and knowledge, also known as Decisional Deskilling, constitutes a significant threat to knowledge workers in the interactions with intelligent Decision-Support Systems (iDSS). The study used an online survey to test six hypotheses for examining the relationship between the extent use of intelligent decision-support systems and the impact on financial professionals' knowledge. The findings support the idea that extensive iDSS use decreases declarative and procedural knowledge. Therefore, balancing technology use with preserving employee skills and knowledge is vital. Proposed mitigation techniques include training and support programs, monitoring reliance on iDSS, and reevaluating system effectiveness.**

Keywords-decisional deskilling; artificial intelligence; decision-support systems; financial services; mitigation techniques.

I. INTRODUCTION

The increasing adoption of intelligent Decision-Support Systems (iDSS) in various industries, including healthcare and finance, has raised concerns regarding their impact on knowledge workers and their decision-making skills [1]-[3].

Decision-Support Systems (DSS) encompass any computerized system that assists with decision-making in organizations [4]. Emerging technologies, such as artificial intelligence have influenced the current DSS landscape [5], demanding a concept extension of the research field into iDSS. Artificial Intelligence (AI), which is also known as "machine intelligence", is a field in computer science that aims to develop systems capable of performing tasks that typically require human intelligence [6]. By using algorithms to learn from data, Machine Learning (ML) enables task automation [6]. According to [7] decision-making processes in organizations include 1) issue identification and problem finding, 2) decision question specification and problem formulation, 3) alternative generation and evaluation, 4) choice and 5) implementation. An iDSS that uses ML can perform any or all these phases. Despite the widespread use of DSS, there is limited research on the impact of iDSS on decision-making under these novel conditions [7][8].

iDSS implementation in organizations alters individual information processing and decision making [9] and can cause unintended deskilling [10]. This study defines this phenomenon as Decisional Deskilling (DD), which involves a decline in decision-making abilities and knowledge loss [1][11]. Literature suggests that DD is often caused by over-reliance on technology, also known as automation bias [1][12]. One possible explanation is that humans tend to delegate the responsibility of information seeking and processing to iDSSs, resulting in reduced individual effort [13]. This can also affect decision-makers' declarative knowledge and procedural knowledge [14]. Declarative Knowledge (DK) is "the storage of fact and events," whereas the memory of Procedural Knowledge (PK) "is more like a technique applied when necessary" [15]. For effective decision making, both types of knowledge, i.e., knowing the "What" and the "How" of the specific task are relevant [15].

[16] discovered that DD may only become apparent when iDSSs are discontinued, even though it can occur on a latent level. Prior research has therefore mainly focused on reliance and its short-term effects. [1] explored the impact of iDSS on DM and defined reliance based on factors, such as user's experience level, problem complexity, familiarity with the iDSS, and cognitive fit. In a case study of a German bank group with a fully automated iDSS [2] found that loss of critical thinking, knowledge, and expertise, as well as misuse of the system, were unintended employee-related short-term effects. [14] used a qualitative approach to investigate partially automated iDSS and identified three factors that reduce auditors' DK and PK, namely, the extent to which the tool takes over routine tasks, the auditors' reliance on the tool, and the time spent with iDSS.

Expanding on [14] this study explores the relation between the extent use of iDSS and financial professional's knowledge. Objectives were to 1) identify contributing factors, 2) assess the impact on professionals' knowledge, and 3) inform mitigation strategies. The paper is organized as follows: Section II outlines the empirical method, Section III presents survey results, Section IV discusses findings and implications, and Section V concludes.

 ISBN: 978-1-68558-077-3

II. METHOD

The study adopted a quantitative empirical approach and employed an online survey for data collection. Figure 1 shows the research framework based on [14].

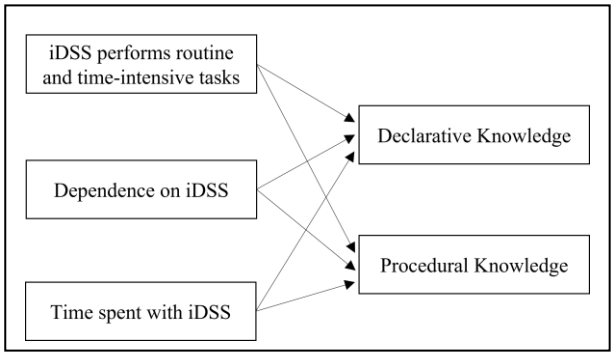

Figure 1. .Research Framework

A. Sampling and Data Collection

Sampling involved professionals from the financial services sector in Germany, encompassing investment banking, commercial banking, asset management, insurance, and other financial services. The additional criteria included experience in decision making, familiarity with DSS, and usage of partially or fully automated iDSS in their current role. These iDSS could be deployed to aid decision-making processes in risk management, fraud detection, portfolio management, credit scoring and underwriting, as well as financial forecasting and modeling. Data was collected through an anonymous online survey between 15th November to 15th December 2022, resulting in 39 completed questionnaires. The survey consisted of questions from the research framework, outlined in Table I, along with open-ended inquiries regarding access to training and support programs, and the participants' experiences with iDSS.

B. Data Analysis

To test the indicated relations of the three potential contributing factors and their impact on declarative and procedural knowledge, six initial hypotheses were built. The collected questionnaire data concerning the items for hypothesis testing were imported and computed using the software SPSS Statistics 28.0.1. In the first step, a null hypothesis and an alternative hypothesis were built for each of the hypotheses:

$$H_0: \rho = 0 \quad (1)$$

$$H_A: \rho \neq 0 \quad (2)$$

The Greek letter ρ indicates the population correlation, i.e., corresponding to the sample Pearson correlation coefficient r. The expression (1) of the null hypothesis H_0 means that Pearson coefficient equals zero, suggesting no association between the two tested variables. Based on the assumption that there is an association between the two variables, the alternative hypothesis H_A requires the coefficient to be different from zero as shown in (2). In the second step, the correlation coefficient r, two-tailed, was calculated and the strength of the correlation between both variables were determined according to Table II. In the next step, the statistical significance was determined by calculating the value of p. A relation is considered statistically significant if the calculated value of p is lower than alpha, with a predefined value of $\alpha < 0.05$. A qualitative content analysis and additional word frequency computations in R were used to examine the answers to the open questions.

TABLE I. QUESTIONNAIRE (EXCERPT)

Question	Item
Years of experience with IT tools for decision making?	Time spent with iDSS[a]
Which best describes the use of IT tools in your decision making?	iDSS performs routine &time-intensive tasks
How much do you feel that you rely upon IT-enabled support tools in carrying out your work?	Dependence on iDSS
Do you believe that your ability to recall details recorded in the IT tool (for example, customer data or financial data) is impacted as a result of your use of IT tool?	Declarative Knowledge
Do you believe that your ability to run your working tasks without the IT tools is impacted as a result of your use of the IT tools?	Procedural Knowledge

a. Multiple choice with single answer: 1) < 2 years, 2) 2 - 3 years, 3) 3 - 5 years, and 4) > 5 years
b. Multi select answers possible. Stages included: 1) Gathering information, 2) Identifying problems, 3) Developing options 4), Selecting the best course of actions, and 5) Implementing the decision.

TABLE II. THE SCALE OF PEARSON'S CORRELATION COEFFICIENT

Value of Coefficient *r*	Correlation
$0 \leq r \leq 0.1$	No Correlation
$0.1 \leq r \leq 0.29$	Low Correlation
$0.3 \leq r \leq 0.49$	Medium Correlation
$0.5 \leq r \leq 0.69$	High correlation
$0.7 \leq r \leq 1.0$	Very High Correlation

III. RESULTS

This study analyzed survey responses from 39 financial services professionals to determine the correlation and statistical significance among variables. The correlation results are summarized in Table III. Further insights were gathered from open questions on training and support programs, and participants' experiences with iDSS.

A. Hypothesis Testing

The study found significant correlations between "iDSS performs routine and time-intensive tasks" and "Declarative Knowledge", as well as "iDSS performs routine and time-intensive tasks" and "Procedural Knowledge", with medium effect sizes. These associations were statistically significant at the 0.05 level, indicating a probability of less than 5% that the null hypothesis, H_0, was correct. Thus, H_0 was rejected in favor of H_A, for both cases, providing support for hypotheses H_1 and H_2 as shown in Table IV.

Moreover, "Dependence on iDSS" showed a high correlation with both "Declarative Knowledge" and "Procedural Knowledge", with correlation coefficients of 0.63 and 0.66, respectively. These associations were statistically significant at the 0.05 level with a p-value of less than .001. As a result, H_0 was rejected in favor of H_A, providing support for hypotheses H_3 and H_4.

TABLE III. RESULTS OF CORRELATIONS

Contributing Factors	Declarative Knowledge		Procedural Knowledge	
	N=39		N=39	
	r	*p*	*r*	*p*
iDSS taking over decision making activities	**0.37**[a]	**.019**	**0.37**[a]	**.021**
Dependence on iDSS	**0.63**[a]	**< .001**	**0.66**[a]	**< .001**
Time spent with iDSS	-0.09	.588	-0.03	.853

a. Correlation is statistically significant at the 0.05 level (2-tailed)

TABLE IV. HYPOTHESES RESULTS

Hypothesis	Result
H_1 The greater the extent to which the iDSS performs routine and time intensive tasks, the less declarative knowledge possessed by the financial professional.	Supported $p = .019$
H_2 The greater the extent to which the iDSS performs routine and time-intensive tasks, the less procedural knowledge possessed by the financial professional.	Supported $p = .021$
H_3 The greater the financial professional's dependence on the intelligent system the less declarative knowledge possessed by the financial professional.	Supported $p = < .001$
H_4 The greater the financial professional's dependence on the intelligent system the less declarative knowledge possessed by the financial professional.	Supported $p = < .001$
H_5 The greater the time the financial professional has spent with the intelligent system, the less declarative knowledge by the financial professional.	Not supported $p = .588$
H_6 The greater the time the financial professional has spent with the intelligent system, the less procedural knowledge by the financial professional.	Not supported $p = .853$

However, the negative correlations that were observed between "Time spent with iDSS" and "Declarative Knowledge" as well as "Time spent with iDSS" and "Procedural Knowledge" were not statistically significant. Hence, H_0 could not be rejected for both cases, and thus, hypotheses H_5 and H_6 were not supported in the sample.

B. Training and Support Programs

The survey question on access to training and support programs for skill development in the working field found diverse responses. Some financial professionals have access to various programs, while others do not require any training due to fully automated software. Employers offer different types and modes of programs, such as internal academies with basic and advanced trainings, mentoring, and online courses, and some are setting up new programs due to the implementation of new software. Other participants reported that their employers offer soft skills, hard skills, and new technology training, as well as career development and coaching. Some also offer career consultation. Participants with access to training programs, stressed the importance of these programs in maintaining and improving skills. While some have access to technology-outdated programs, others do not use any offered by their employer.

C. Training and Support Programs

The finance professionals surveyed responded with a range of experiences and opinions on iDSS. Some found automation helpful in focusing on clients, while others felt pressure and risk of deskilling. The systems in place helped some organize their work, but others found the information superficial and not useful. Many said their organizations still had a traditional mindset despite technological changes, and they needed more training on the impact of new technology. Some found it challenging to understand the information provided by the software and explain their decisions. A few expressed concerns over the limited control they had over the software and its decisions. Some found automated systems convenient, but others found them difficult to navigate with overwhelming amounts of customer data. Difficulty in explaining decisions to other internal stakeholders due to the confusing solutions of systems and superficial answers to problems were also mentioned.

IV. DISCUSSION

The results showed significant associations between two of the three contributing factors and financial professionals' declarative and procedural knowledge, supporting four of the six hypotheses according to Table IV. The survey responses show a diverse range of experiences and opinions on iDSS, access to training and support programs for skill development.

A. Interpretation of the Findings

While some employers offer a variety of internal and external training and support programs, few participants have no access to training programs. Other participants feel they do not need them due to the ease of automated systems in place. Those with access emphasize their importance in maintaining and developing their skills. Some financial professionals appreciate technology's assistance, while others feel pressure to make quick decisions, struggling with the limitations and difficulty in navigating the systems in place effectively, and risking deskilling.

The results showed a significant association between financial professionals' dependence on the iDSS and a decrease in their DK and PK. In addition, there is a significant association between iDSS taking over routine and time-intensive tasks in decision making and a decrease in financial professionals' DK and PK. However, no significant association was found between time spent with the iDSS and DK and PK. Overall, the results suggest that a greater reliance on iDSS leads to a decrease in financial professionals' knowledge.

 ISBN: 978-1-68558-077-3

B. Theoretical and Practical Contributions

The theoretical contribution of this research lies in its examination of the relationship between the extent of use of iDSS and the knowledge possessed by financial professionals. By exploring this relationship, the study provided insights into potential contributing factors. The results indicate that the use of iDSS in organizations can notably influence the financial professionals` knowledge.

The findings of the study highlight the importance of striving for a balance between technology use and maintaining a capable workforce. Mitigation techniques to address DD include providing proper training resources and programs to support employee growth and development, as well as encouraging participation among employees. As AI becomes more prevalent in decision-making processes, monitoring employees' reliance on intelligent decision aids becomes crucial to identify areas where additional training and support is needed. By offering knowledge workers opportunities to participate in purely human decision making, organizations can further counteract the loss of specific task knowledge and skills. Finally, to ensure iDSS remains a supportive tool for decision making, the effectiveness of the system in place should be regularly reevaluated and information processes be adjusted accordingly.

C. Limitations

This study has several limitations that should be acknowledged. Firstly, the sample size of 39 finance professionals is relatively small, which may limit the generalizability of the results to other industries, organizations, or larger populations. Secondly, the findings of the study are based on the participants' own opinions and ratings, which may introduce some bias into the results. Additionally, these opinions and ratings are time-sensitive, which may impact the applicability of the results in the future. Lastly, this study only examined three contributing factors to decisional deskilling and did not consider other individual, technical, and organizational factors.

V. CONCLUSION AND FUTURE WORK

By studying the relation between the extent use of iDSS and the knowledge possessed by financial professionals, the study found significant associations of the two contributing factors “iDSS takes over routine and time-intensive taks” and “Dependance on iDSS” with DK and PK. However, there was no significant association with the variable of “Time spent with iDSS”. The results also revealed varied experiences and opinions on iDSS, as well as on participants’ access to training and support programs. Some professionals appreciated technology's assistance, while others felt pressure to make quick decisions and struggled with the limitations of the IT tool in place.

The study highlights the potential drawbacks of over-relying on emerging technology for decision-making and emphasizes the need to mitigate potential negative impacts on workforce knowledge and skills. The results can be used to raise awareness of the significance of providing proper resources and programs to support employee growth and development, and to encourage organizations to invest in these resources. Mitigation strategies includes increasing participation in human decision-making activities, monitoring employees' reliance on iDSS, and reevaluating the effectiveness and efficiency of the system in place present further mitigation strategies to address DD.

Future research could benefit from a longitudinal study tracking the effects of DD over time and combining survey data with methods, such as interviews or case studies to gain a deeper understanding of the concept of DD.

ACKNOWLEDGMENT

The author likes to thank Olga Levina and the reviewers for their constructive feedback. Any opinions expressed in this article are those of the author.

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 ISBN: 978-1-68558-077-3