Title

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Choose and Use: Users' Selection of Information Sources for Decision Support

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Abstract

Intelligent systems that record, analyze, and respond to events have become major parts of our lives. They are available as Decision Support (DS) for many tasks and can enhance the information on which decision-makers can base their decisions. Decision makers need to evaluate the available information, and they also have to decide whether to seek information from additional information sources. The information is often costly, and its costs and benefits must be weighted. Also, integrating information from multiple sources can complicate the decision task. Here, we study the combined decision process that chooses information sources and integrates them, if chosen, in a classification decision. In an online experiment with 75 engineering students, we manipulated the redundancy level of information received from DS with already existing information. Participants' task in two between-subjects conditions was to classify binary events with the option to access up to two DS systems. In one of the conditions, the two DSs provided non-redundant information, and in the second condition, one of them provided fully redundant information, and the other provided non-redundant information. We found that the decision to access information was not affected by whether some information was redundant (strongly correlated with already available information). Participants used the information to improve classification performance, and the improvement was significantly higher when they used non-redundant information. However, the benefits gained were smaller than predicted from a normative model. Moreover, the use of information from multiple non-correlated sources can increase mental workload, as was evident in our results, possibly because of conflicting information from different sources.

Keywords: Alerting systems, Decision making, Decision support

Introduction

The advances in technology and the variety of available information sources make it easier to obtain information. However, the availability of the information requires choosing whether and which information source to use. The decision depends to some extent on the redundancy of the new information, considering the currently available information (i.e., the level of correlation with already available information) (Liang & Fu, 2017; Mulugeta, Ben Yaakov, & Meyer, 2022). Information acquisition decisions have been studied extensively, and the main conclusion from the literature is that people tend to make non-optimal decisions (Ho, Hagmann, & Loewenstein, 2021; Ben-Yaakov, Bitan, & Meyer, 2021). According to Bartoš et al. (2014), implicit biases in information gathering can influence information accumulation processes, potentially leading to inefficient choices due to incomplete or biased assessments (Bartoš, Bauer, Chytilová, & Matějka, 2016). Consistent with expectations, participants showed a preference for using a more reliable DS over a less reliable one (Montanari & Nunnari, 2023) and showed the ability to distinguish when it is worth purchasing information (Ben Yaakov, Wang, Meyer, & An, 2019). However, a recent study show empirical evidence that users sometimes access information even when it is not beneficial, and conversely, at times, they do not access information that could be beneficial to them (Ben-Yaakov et al., 2021) From a normative perspective, when using two (or more) sources of information, non-redundant (uncorrelated) information should be preferred to minimize forecast error and to prevent shared biases (Hogarth, 1989; Soll, 1999; Yaniv, 2004). Recent studies indeed found that the redundancy of information was negatively correlated with its use (Liang & Fu, 2017; Mulugeta et al., 2022). This is in line with older studies, which found that people correctly recognize non-redundant information as more valuable (Goethals & Nelson, 1973; Gonzalez, 1994). However, some evidence suggests that people prefer redundant information (Kahneman & Tversky, 1973). This tendency may be linked to the phenomenon of *confirmation bias*, where individuals preferentially seek evidence that confirms their beliefs rather than evidence that contradicts them. Strong evidence supporting the presence of confirmation bias in decisions related to information acquisition and use has been documented, and this bias has been found to be resilient even with increased experience (Jones & Sugden, 2001).

The use of DS has been shown to enhance performance (Ben-Yaakov et al., 2021; Dixon, Wickens, & McCarley, 2007; Rieger & Manzey, 2022). However, the effect of correlated information on performance is a contentious issue. While some studies suggest that performance worsens with correlated information compared to uncorrelated information (Elvers & Elrif, 1997), others argue that the level of correlation between DS information and already existing information has no significant effect on performance (Munoz Gomez Andrade, Duncan-Reid, & McCarley, 2022). Moreover, the decision to use DS with more or less correlated information can also impact operators' workload. It has been observed that operators report a lower subjective workload when they are aided by

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automation (Balfe, Sharples, & Wilson, 2015; Röttger, Bali, & Manzey, 2009). Previous studies extensively explored the dynamics of user interaction with Decision Support (DS) systems and their implications on decision-making processes. One study investigated how the redundancy of information provided by DS influences users' decisions to purchase and trust it and their actual performance in a classification task (Mulugeta et al., 2022). The findings revealed a clear preference among participants for a non-redundant DS (non-correlated information) over partly or fully redundant DS, with better performance and higher trust when using non-redundant DS. A later study that built on these insights delved deeper into the impact of the correlation between DS and already available information on user preferences, performance, and trust (Ben Yaakov, Denisova, Mulugeta, & Meyer, 2024). They investigated five levels of redundancy: no redundancy, low, medium, high, and fully redundant (fully correlated) information. Additionally, they examined three levels of DS quality: low, medium and high. Results showed that participants accessed DS more, the less redundant it was, and the higher its quality, suggesting a recognition of the value of unique content and quality of information. Interestingly, results also indicated that correlated information could diminish performance, with the effect on subjective trust being contingent on the DS quality level (Mulugeta et al., 2022). These studies highlighted a trend towards normative preferences in decision support rather than a reliance on confirmatory information. Collectively, they contribute to a nuanced understanding of how information characteristics in DS affect user decisions, trust, and performance in decision-making scenarios.

MODEL

We use Signal Detection Theory (SDT) (Green, Swets, et al., 1966; Hautus, Macmillan, & Creelman, 2021; Wickens, 2001) to model the binary classification decisions by both a human and a binary Decision Support (DS) system. The probability of a signal is p_s, and the probability of noise is $p_n = 1 - p_s$. The probability that the DS correctly detects a signal event and raises an alarm (i.e., true positive) is P_{TP}^{DS}, and P_{FP}^{DS} is the probability that the DS incorrectly issues an alert when the event is noise (i.e., false positive). The probabilities of false negative and true negative are denoted by P_{FN}^{DS} and $P_T N^{DS}$, respectively, where $P_{FN}^{DS} = 1 - P_{TP}^{DS}$; $P_{TN}^{DS} = 1 - P_{FP}^{DS}$. SDT differentiates between the detection sensitivity of a sensor (human or DS) and its response bias (decision threshold). The detection sensitivity (d') is the sensor's ability to distinguish between signal and noise. It is represented by the shift of the signal probability density function compared to the noise probability density function. When $d^{'} = 0$, the sensor is unable to distinguish between signal and noise. As d' increases, the ability to differentiate between the two entities increases. The classification probabilities depend on the detection sensitivity and the DS decision threshold (β^{DS}). While the sensitivity is a given property of the detectors, the decision threshold can be adjusted. Its optimal setting depends on p_s and the outcome values from the possible classifications ($V_{TP}, V_{FP}, V_{TN}, V_{FN}$). For a single detector, it is: $\beta = \frac{p_n}{p_s} \cdot \frac{V_{FP}-V_{TN}}{V_{FN}-V_{TP}}$

The human classifies the event as "Signal" or "Noise," given information about the event and the DS output. When using DS, the human decision variables are $\langle \beta_A^H, \beta_{\bar{A}}^H \rangle$, which are the thresholds for classifying events when the DS indicates a signal event (alarm) or noise event (no alarm), respectively. Therefore, we can compute the human classification probabilities when an alarm was issued ($P_{TP|A}^H, P_{FP|A}^H, P_{TN|A}^H, P_{FN|A}^H$) and when no alarm was issued ($P_{TP|\bar{A}}^H, P_{FP|\bar{A}}^H, P_{TN|\bar{A}}^H, P_{FN|\bar{A}}^H$).

When using two DSs, the human decision variables are $\langle \beta_{A_1 A_2}^H, \beta_{A_1 \bar{A_2}}^H, \beta_{\bar{A_1} A_2}^H, \beta_{\bar{A_1} \bar{A_2}}^H \rangle$, which specifies the thresholds to classify events based on the output of the two DSs. We assume that events are independent and identically distributed (IID), and a decision for one event does not affect decisions regarding other events.

Expected Value

We can compute the expected value without DS, with one DS, or with two DS.

Without DS

$$EV(\beta^H) = p_s \cdot (P_{TP}^H \cdot V_{TP} + P_{FN}^H \cdot V_{FN}) + p_n \cdot (P_{FP}^H \cdot V_{FP} + P_{TN}^H \cdot V_{TN})$$

With one DS

$$\begin{aligned} EV(\beta^{DS}, \beta_A^H, \beta_{\bar{A}}^H, C_1, C_2) = \\ p_A \cdot [P(S|A) \cdot (P_{TP|A}^H \cdot V_{TP} + P_{FN|A}^H \cdot V_{FN}) + \\ P(N|A) \cdot (P_{FP|A}^H \cdot V_{FP} + P_{TN|A}^H \cdot V_{TN})] + \\ p_{\bar{A}} \cdot [P(S|\bar{A}) \cdot (P_{TP|\bar{A}}^H \cdot V_{TP} + P_{FN|\bar{A}}^H \cdot V_{FN}) + \\ P(N|\bar{A}) \cdot (P_{FP|\bar{A}}^H \cdot V_{FP} + P_{TN|\bar{A}}^H \cdot V_{TN})] - C_i \end{aligned}$$

With two DS

$$\begin{aligned} EV(\beta^{DS}, \beta_{A_1,A_2}^H, \beta_{\bar{A_1},A_2}^H, \beta_{A_1,\bar{A_2}}^H, \beta_{\bar{A_1},\bar{A_2}}^H, C_1, C_2) = \\ p_{A_1,A_2} \cdot [P(S|A_1,A_2) \cdot (P_{TP|A_1,A_2}^H \cdot V_{TP} + P_{FN|A_1,A_2}^H \cdot V_{FN}) + \\ P(N|A_1,A_2) \cdot (P_{FP|A_1,A_2}^H \cdot V_{FP} + P_{TN|A_1,A_2}^H \cdot V_{TN})] + \\ p_{A_1,\bar{A_2}} \cdot [P(S|A_1,\bar{A_2}) \cdot (P_{TP|A_1,\bar{A_2}}^H \cdot V_{TP} + P_{FN|A_1,\bar{A_2}}^H \cdot V_{FN}) + \\ P(N|A_1,\bar{A_2}) \cdot (P_{FP|A_1,\bar{A_2}}^H \cdot V_{FP} + P_{TN|A_1,\bar{A_2}}^H \cdot V_{TN})] + \\ p_{\bar{A_1},A_2} \cdot [P(S|\bar{A_1},A_2) \cdot (P_{TP|\bar{A_1},A_2}^H \cdot V_{TP} + P_{FN|\bar{A_1},A_2}^H \cdot V_{FN}) + \\ P(N|\bar{A_1},A_2) \cdot (P_{FP|\bar{A_1},A_2}^H \cdot V_{FP} + P_{TN|\bar{A_1},A_2}^H \cdot V_{TN})] + \\ p_{\bar{A_1},\bar{A_2}} \cdot [P(S|\bar{A_1},\bar{A_2}) \cdot (P_{TP|\bar{A_1},\bar{A_2}}^H \cdot V_{TP} + P_{FN|\bar{A_1},\bar{A_2}}^H \cdot V_{FN}) + \\ P(N|\bar{A_1},\bar{A_2}) \cdot (P_{FP|\bar{A_1},\bar{A_2}}^H \cdot V_{FP} + P_{TN|\bar{A_1},\bar{A_2}}^H \cdot V_{TN})] - C_1 - C_2 \end{aligned}$$

Where P_A, p_{A_1,A_2} are the probabilities that DS_i will raise an alarm and C_i is the cost to purchase DS i. A rational decision-maker will maximize the expected value.

STUDY

In this study, we examine the effect of DS's redundancy level (i.e., the correlation between the DS output and already available information) on the decision to purchase up to two DS, the effective sensitivity,and the score as performance indicators, and the cognitive workload, measured with NASA-TLX questionnaire (Hart & Staveland, 1988). Our empirical study was guided by the normative model developed to predict the behavior of a perfectly rational decision-maker. This model, based on standard utility theory, was used to calculate the expected value of utilizing different combinations of DS systems, with varying levels of redundancy (see Table 1 for model predictions). Normatively, non-redundant information should be valued higher, as it provides more unique information than partly or fully redundant information. However, users may prefer confirmative information and use the additional information to validate prior opinions and to make their decisions with greater subjective certainty. We predict better performance for participants who use non-redundant systems than participants who use a redundant DS or do not use a DS. Moreover, we expect better performance among participants using two non-redundant systems than one redundant and one non-redundant system. Regarding workload, as indicated by (Balfe et al., 2015; Röttger et al., 2009), we expect that participants with DS will report a lower workload compared to participants without DS. Moreover, we expect that participants aided by non-redundant systems will experience a greater workload due to the potential of events with conflicting information, as previously reported by (Imants, Theeuwes, Bronkhorst, & Martens, 2021).

METHOD

Participants

Seventy-five engineering students participated in the experiment as part of a human factors course.

Apparatus

We developed the experiment as a web-based system with a back-end side implemented with a Python infrastructure (using the Django library), a database (MySQL), and a front-end side developed in HTML. Participants performed the experiment on their own devices.

Procedure

Participants were asked to take on the role of a physician and monitor patients' medical conditions. They were to decide whether an intervention was necessary or not. A patient's medical condition was represented by a number, which reflects the probability that a medical intervention is needed. Participants were briefed on the possibility of purchasing up to two Clinical Decision Support Systems (CDSSs) containing information about the patient's condition. The experiment started with instructions explaining the task. After the instructions, participants began the experiment, which consisted of 5 blocks. At the beginning of each block, they decided whether and which CDSSs to purchase from a set of 2 CDSSs. Participants were informed about the system's classification probabilities (i.e., true positive rate and false positive rates). After they decided whether and which systems to purchase, they classified 30 events based on the observed value (which simulates the patient's medical condition) and the output of the CDSSs, if purchased. The sequence of event types (patient needed medical intervention or not) and the information about the patient's condition were the same in both conditions. After each experimental block, participants answered the NASA-TLX questionnaire. The flow of the experiment can be seen in Figure 1 and Figure 2 shows a typical classification screen. Participants purchased CDSSs with a point system. They began each block with a budget of 30 points. They earned 3 points if they correctly identified whether an intervention was needed. They lost 6 points if they did not correctly identify the need for an intervention and 3 points when they intervened when it was unnecessary. Participants received feedback on the classification immediately after classifying the event. The first two blocks were used as training blocks, in which the participants could familiarize themselves with the task and the CDSSs, and we only analyzed blocks 3, 4, and 5. The CDSSs were counterbalanced between participants.

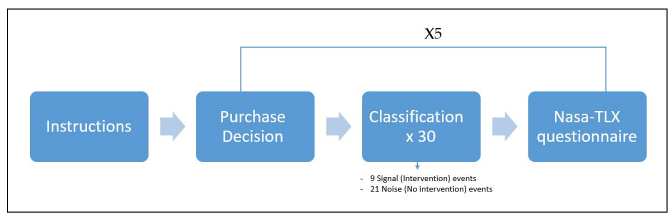

Figure 1: Experiment Flow

Figure 2: Typical classification screen with both CDSSs, CDSS A only, CDSS B only or no CDSS at all (left to right).

Experimental Design

Conditions The two experimental conditions differed in the correlation between the information about the patient's condition and the CDSSs information. In the "all non-redundant condition," the two CDSSs provided non-correlated information. In the "one redundant condition", one of the systems provided information that was fully correlated with the information about the patient's condition and the second system was not correlated. The 2 systems were independent to each other. We manipulated the correlation between the CDSSs and the participants' observed values with the equation: $Y = r \cdot X + \sqrt{1-r^2} \cdot z$ citekaiser1962sample. In the non-redundant condition, the purchase of both systems had positive value, while in the partly redundant condition, one should only purchase the non-redundant system, as can be seen in Table 1.

Parameters The probability that a patient needed a medical intervention was p = .3. In both conditions, the CDSSs had the same decision thresholds and sensitivity (d' = 1.5). The participants' information about a patient's condition was sampled from one of two normal distributions with means of 5.25 and 6.75 for noise (no intervention needed) and signal (intervention needed), respectively. The standard deviation for both distributions was 1. Thus, the participant's sensitivity in SDT terms was d' = 1.5, and the information was displayed on a [2,10] scale. The CDSS information was also sampled from one of two normal distributions with means of 5.25 and 6.75, so the d' of the systems was also 1.5.

Exclusion criteria Six participants with a sensitivity of $d' = 0$ or lower in one of the analyzed blocks (blocks 3-5) were excluded from the analysis.

Table 1: Expected value depends on the purchase decision

Decision	Expected Value
No CDSS	75
1 Dependent CDSS	70
1 Dependent & Independent CDSS	77
1 Independent CDSS	82
2 Independent CDSS	84.5

RESULTS

Purchase Decision

Chi-square tests for independence were conducted to examine the relationship between the experimental condition (all non-redundant vs. one redundant) and the Purchase Decision (PD) across each of the three blocks (Blocks 3-5). In all blocks, no significant relationship was observed between the PD and the experimental condition. We also conducted Chi-square tests for goodness of fit for each Condition and Block separately to test whether participants' purchase decisions were distributed uniformly. As can be seen in Figure 3 and Table 2, among participants in the non-redundant condition, in Block 5, participants' purchase decisions were not uniformly distributed. Participants had a higher tendency to purchase two systems (M = .54) compared to one system (M = .27) or no systems (M = .19). In the non-redundant condition in blocks 3 and 4 and the one-redundant condition in all three blocks, there was no significant deviation from a uniform distribution of purchase decisions. Further analyses were conducted to determine if there was a significant preference for either the redundant or non-redundant CDSS when participants in the 'one redundant condition' opted to purchase only one CDSS. This analysis revealed no significant preference in any of the three blocks. In Blocks 3 and 4, an equal proportion of participants who chose to purchase only one CDSS opted for the redundant CDSS as those who chose the non-redundant CDSS. However, in Block 5, among participants who decided to purchase only one CDSS, 27.3% chose the redundant CDSS, while 72.7% selected the non-redundant CDSS.

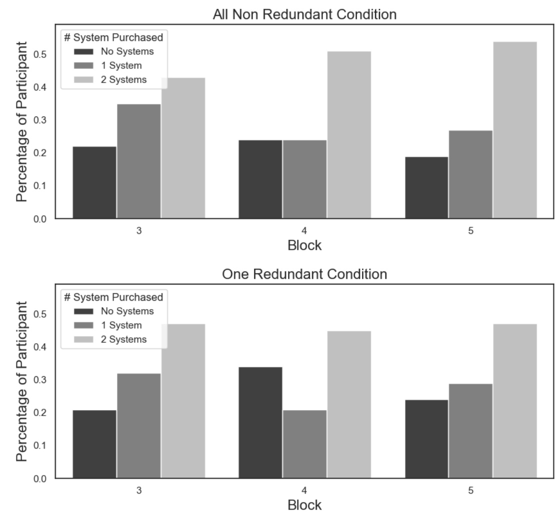

Figure 3: PD distribution by Block and Condition.

Table 2: Chi-Square test for goodness of fit

	Block	χ^2	df	p
All non-redundant Condition	3	2.65	2	.27
	4	5.405	2	.07
	5	7.51	2	.02
One redundant Condition	3	4	2	.135
	4	3.21	2	.2
	5	3.53	2	.17

Performance

We computed the effective sensitivity (d') and score for each participant in each block and analyzed it with a Generalized Linear Mixed Model (GLMM) with the participant's ID as a random effect, the Condition and Purchase Decision (PD) as fixed effects and the Block as a repeated measure variable.

Sensitivity The main effects Condition $F(1,219) = 7.66, p = .006$, and PD, $F(2,219) = 7.66, p = .006$, and the interaction Condition X PD, $F(2,219) = 8.83, p < .001$, were significant. Participants in the all non-redundant condition differentiated better between signal and noise events (i.e., they had a higher effective sensitivity) ($M = 1.73, SD = .065$), compared to participants in the one-redundant condition ($M = 1.44, SD = .05$). Pairwise contrasts between the number of purchased systems (zero, one or two) showed that participants who purchased no systems had significant lower effective sensitivity ($M = 1.13, SD = .05$), compared to participants who purchased one system ($M = 1.37, SD = .06$) and two systems ($M = 1.94, SD = .06$), $Adj.p < .01, Adj.p < .001$, respectively, as can be seen in Figure 4. A significant difference was also found between participants who purchased one system and two systems, $Adj.p < .001$. Pairwise contrasts were also used to further analyze the interaction between PD X Condition. Results showed that among participants who purchased two systems, participants in the all non-redundant condition had a significantly higher effective sensitivity ($M = 2.2, SD = .08$), compared to participants in the one-redundant condition, in which one system was strongly correlated with the available information and the other was independent, ($M = 1.67, SD = .07$), $Adj.p < .001$.

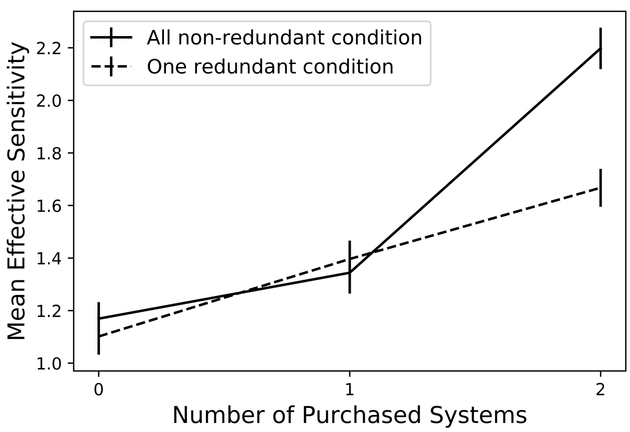

Figure 4: Mean effective Sensitivity by Purchase Decision and Condition.

Score The main effects Condition $F(1,219) = 6.1, p = .01$, and PD, $F(2,219) = 14.27, p < .001$, and the interaction Condition X PD, $F(2,219) = 5.43, p = .005$, were significant. Participants in the all non-redundant condition achieved higher scores ($M = 69.88, SD = 1.33$), compared to participants in the one-redundant condition ($M = 63.94, SD = 1.14$). Pairwise contrasts between the number of purchased systems (zero, one, or two) showed that participants who purchased no ($M = 61.22, SD = 1.54$) or one ($M = 63.76, SD = 1.63$) system, achieved significantly lower scores, compared to participants who purchased two systems ($M = 71.5, SD = 1.27$), $Adj.p < .001$, as can be seen in Figure 5. Pairwise contrasts were also used to further analyze the interaction between Purchase Decision and Condition. Results showed that among participants who purchased two systems, participants in the all non-redundant condition had significantly higher scores ($M = 76.84, SD = 1.64$), compared to participants in the one-redundant condition, ($M = 65.96, SD = 1.65$), $Adj.p < .001$.

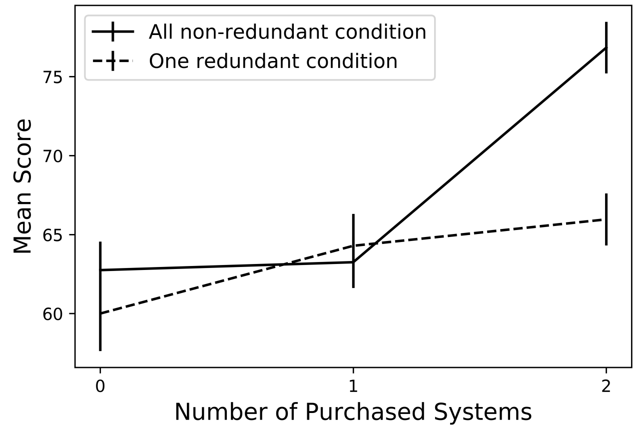

Figure 5: Mean score by Purchase Decision, and Condition.

Workload

We measured participants' workload in the task using the NASA-TLX questionnaire. We computed the workload for each participant in each block and analyzed it similarly to previous analyses. There was a significant effect of the PD, $F(2,219) = 3.98, p = .02$ and the interaction Condition X PD, $F(2,219) = 3.74, p = .025$. Pairwise contrasts between the number of purchased systems (no, one or two) showed that participants who purchased no system reported significantly lower workload ($M = 6.32, SD = 0.4$), compared to participants who purchased one ($M = 7.5, SD = 0.5$) or two ($M = 7.98, SD = 0.35$) systems $Adj.p = .05, p = .005$, respectively. Pairwise contrasts showed that among participants with two systems, participants in the all non-redundant condition reported significantly higher workload ($M = 8.59, SD = .52$), compared to participants in the one-redundant condition ($M = 7.34, SD = .45$), $Adj.p = .05$, as can be seen in Figure 6.

Discussion

We developed a normative model specifically designed to determine the optimal purchasing decisions when users are faced with multiple Decision Support (DS) systems, as well as to predict the expected performance based on purchasing strategy. The model takes into account the properties of the DSs, the human, and the environmental state. To assess the model's effectiveness, we conducted an experiment to collect behavioral data and compared this with the model's predictions. The primary aim of our study was to gain insights into users' preferences for DSs, particularly in scenarios where they must choose between systems offering different levels of redundant information. Furthermore, we explored how their choices impacted the overall performance of the DS and the users' subjective workload.

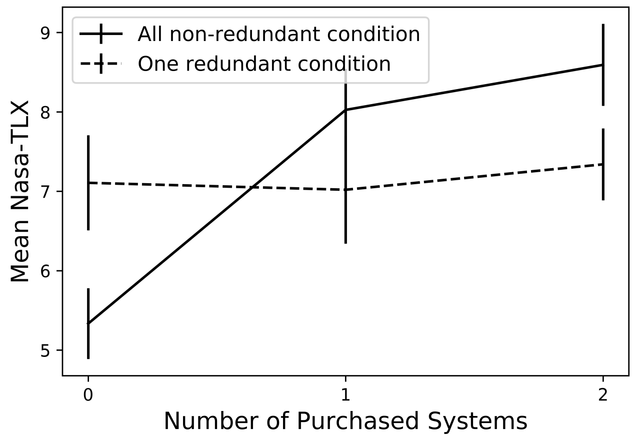

Figure 6: Mean workload by Purchase Decision, and Condition.

Participants demonstrated a tendency to purchase information from the DS, regardless of the potential benefits and the redundancy level of the information. These findings are consistent with previous studies indicating non-optimal information acquisition decisions (Ben Yaakov et al., 2019; Ho et al., 2021).

When comparing the results of the current study with previous research (see (Mulugeta et al., 2022; Ben Yaakov et al., 2024)), intriguing patterns and contrasts are observed. Previously, a distinct preference for non-redundant DS was observed, with participants demonstrating better performance and higher trust when using non-redundant DS. This trend aligns with findings from Block 5 of our current study in all non-redundant conditions, where participants exhibited a marked inclination towards purchasing two systems. This consistency underscores the recognized value of non-redundant information. However, the absence of a significant preference for non-redundant DS in the early blocks (3 and 4) and throughout the one-redundant condition presents a notable deviation from past trends. This divergence could be attributed to the experimental design, while in (Mulugeta et al., 2022; Ben Yaakov et al., 2024), the decision between redundancy levels was manipulated as a between-subjects variable, meaning participants were not required to choose between redundant and non-redundant systems. In contrast, our experiment required participants to make this distinction themselves, choosing among purchasing both, one, or no systems. This requirement to differentiate may have been challenging for participants, potentially explaining the observed deviation in their decision-making behavior.

Although participants purchased DS, the utilization of the informationwas not always optimal, resulting in limited benefits from DS potential to enhance performance. This observation aligns with findings from previous studies (Meyer, 2001; Parasuraman, Sheridan, & Wickens, 2008; Rieger & Manzey, 2022; Ben-Yaakov, Meyer, Wang, & An, 2020). We noted that participants' overall sensitivity increased when they purchased one DS, and it further improved with the purchase of two systems. The addition of more information generally led to better performance. Although participants did not differentiate between systems that provided redundant and non-redundant information, the level of redundancy affected performance, as is evident from the significant effect of the experimental condition. When purchasing two systems, participants' performance improved more in the all-non-redundant condition compared to the one-redundant condition, underscoring the value of non-redundant information. Even in the one-redundant condition, using two systems, including a fully redundant one, was beneficial. This improvement may be partly due to the fact that some participants who chose to purchase only one system selected the redundant one, whereas, with two systems, one was always non-redundant.

We also analyzed the participants' workload using the NASA-TLX questionnaire (Hart & Staveland, 1988). Participants with one or two DSs experienced higher workload, compared to participants who did not use a DS. This finding conflicts with previous studies (Balfe et al., 2015; Röttger et al., 2009). A possible explanation for this phenomenon is that processing information from multiple sources may raise workload. When aided by two non-redundant systems, participants reported higher workload compared to participants who used one redundant and one non-redundant system. As explained before in (Imants et al., 2021), this might be due to conflicts between different information sources.

The study highlights the role of redundancy in information acquisition and decision-making processes when individuals have the option to access multiple systems. We observed an interesting preference for non-redundant information sources, which significantly influences both performance and subjective workload. This tendency underscores the critical need for thoughtful consideration of redundancy in the design and implementation of DSs. While potentially beneficial in certain contexts, redundant information can lead to suboptimal decision-making and increased cognitive load.

Our findings highlight the complex interactions between the decisions to use information from different sources that provide more or less redundant information, and its integration into the actual decision processes. In particular, the relation between available and new information must be considered when predicting performance and designing systems. Future research can provide further insights into information acquisition decisions, the use of this information, and its effects on performance and workload.

Acknowledgments

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