Augmented Reality to Reduce Cognitive Load in Operational Decision-Making

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Abstract. Augmented reality (AR) technologies can overlay digital information onto the real world. This makes them well suited for decision support by providing contextually-relevant information to decision-makers. However, processing large amounts of information simultaneously, particularly in time-pressured conditions, can result in poor decision-making due to excess cognitive load. This paper presents the results of an exploratory study investigating the effects of AR on cognitive load. A within-subjects experiment was conducted where participants were asked to complete a variable-sized bin packing task with and without the assistance of an augmented reality decision support system (AR DSS). Semi-structured interviews were conducted to elicit perceptions about the ease of the task with and without the AR DSS. This was supplemented by collecting quantitative data to investigate if any changes in perceived ease of the task translated into changes in task performance. The qualitative data suggests that the presence of the AR DSS made the task feel easier to participants; however, there was only a statistically insignificant increase in mean task performance. Analysing the data at the individual level does not provide evidence of a translation of increased perceived ease to increased task performance.

Keywords: Augmented Reality · Decision-Making · Decision Support System · Cognitive Load · Ease · Performance.

1 Introduction

Decision-making occurs at all levels of an organisation, from long-term strategic decisions down to day-to-day operational decisions. Decision-makers can gain insights from information stored in their memory and surrounding environment to make effective decisions. However, processing large amounts of information simultaneously, particularly in time-pressured conditions, can result in poor decision-making due to cognitive load. The ever-increasing volume of information available with Industry 4.0, coupled with tough demands for rapid and accurate provision of services, place excess cognitive burdens on human operators [14]. Therefore, reducing the cognitive demands of workers is an important and timely goal for Human-Computer Interaction researchers to pursue.

Cognitive Load Theory describes a model of human cognitive architecture centred on a permanent knowledge base in the long-term memory and a temporary conscious processor of information in the working memory [16]. The working memory has limited capacity and duration, so there is a limit to the amount of information that can be held and used in the execution of cognitive tasks [4]. Therefore, decision support systems (DSS) are being designed to alleviate cognitive load by externally providing relevant and appropriate information to decision-makers [29].

DSS can be characterised as "interactive computer-based systems which help decision-makers utilize data and models to solve unstructured problems" [31], although more recent work on DSS extends the definition to include "any computer-based system that aids the process of decision-making" [9]. For example, satellite guided navigation systems, such as GoogleMaps, are DSS that provide insights such as journey distances and traffic conditions to help users decide which route to take between two points.

Many DSS make use of visualisations to communicate complex information with clarity and speed [7, 25, 32]. Situated visualisations provide the benefit of overlaying insightful information onto the problem environment [18]. The information conveyed in situated visualisations could be based on the context, location, objects in view, or sensor data from the environment [15]. Literature suggests that the use of visualisations in this way can act as a substitute for keeping track of information in the working memory – in other words, the visualisations can be used as a form of "external memory" [23]. Situated visualisation can be achieved through traditional visualisation methods, such as placing physical signs and images into the real world. However, augmented reality (AR) provides an opportunity to situate digital information in the real world that can be interacted with and modified in real-time.

AR can be defined as a "human-machine interaction tool that overlays computer-generated information in the real-world environment" [19]. It is seen as the 'middle ground' of the mixed reality spectrum between telepresence (completely real) and virtual reality (VR, completely simulated) [20]. AR usually involves augmenting human vision with context-specific data; although, AR has the potential to be applied to other senses as well. The data overlaid on the real world allows the user to perceive information about objects that cannot be detected with their own senses [1].

A growing amount of literature has been published that investigates AR-based decision-making e.g., [13, 21, 27, 28]. However, the research to date has tended to focus on evaluating the performance of users in a specified application rather than specifically investigating the effects of AR on cognitive load [14]. In addition, existing research tends to investigate the use of AR to provide step-by-step instructions for study participants to follow when completing a task (e.g., [35, 8]) rather than to provide decision support. In these studies, the AR system essentially *substitutes* the cognitive processes of the decision-maker because they no longer have to reason about the solution to the problem. Few studies have investigated the use of AR to *augment* the cognitive reasoning of decision-makers without explicitly providing the solution to a task.

This paper aspires to contribute to the field of augmented cognition by investigating the effects of AR on cognitive load whilst decision-makers complete a task without the provision of step-by-step instructions. It is a widely held view that a more difficult task requires more complex mental operations, thus requiring more processing capacity, resulting in a greater cognitive load [22]. Therefore, the main research aim of this paper is to investigate whether the presence of an augmented reality decision support system (AR DSS) affects decision-makers' perceptions of the ease of completing a task. In addition, a review of the effects of AR systems on mental workload and task performance suggests that "when there are positive effects on mental workload, effects on task performance are most likely to be positive as well" [14]. Therefore, a secondary research aim is to investigate whether any changes in perceived ease of a task translate to changes in performance in the task.

An exploratory user study was conducted to investigate changes to perceived task ease and resulting changes to task performance. This involved recruiting participants to complete a bin packing task with and without the presence of an AR DSS. The research methodology, including the design of the AR DSS and bin packing task, is discussed in Section 2. The results and their implications are discussed in Section 3. Finally, the paper is concluded in Section 4 with a summary and suggestions for future work.

2 Method

The primary research question addressed in this paper investigates cognitive load as follows:

– Does the presence of an augmented reality decision support system (AR DSS) affect decision-makers' perceptions of the ease of completing a bin packing task?

The secondary research question asks:

– Do any changes in perceived ease of the task translate to changes in performance?

The research questions were investigated using a within-subjects experiment. Human participants were asked to complete a variable-sized bin packing task with and without the assistance of an AR DSS. A mixed methods approach was used: qualitative data was collected through semi-structured interviews to investigate the effect of the AR DSS on perceptions of the ease of the task, and quantitative data was collected to investigate the effects on the performance of decision-makers in the task.

2.1 Materials

To evaluate the effects of AR on cognitive load in operational decision-making, two experimental artefacts were designed: a bin packing task involving decision-making to solve a problem, and an augmented reality decision support system (AR DSS).

The Bin Packing Task. Many operational decisions in industry, such as minimising waste in stock-cutting and minimising makespan in machine scheduling, can be modelled using bin packing problems. Such problems consist of a set of items which need to be packed into bins whilst minimising an objective function, such as the number of bins, cost, or excess capacity of used bins. The variable-sized bin packing problem is a variation of the traditional one-dimensional bin packing problem. It consists of a set of items of different sizes (or weights) to be packed into a set of bins, where each bin has a given capacity and cost associated with it. The objective of the variable-sized bin packing problem is to minimise the total cost of packing all the items into the bins.

The problem is formally defined as follows [12]. There is a set J of bins with m different bin types. Each bin type $j, (j = 1, ..., m)$, has two properties: *capacity* b_j and *cost* c_j. A set I of n items must be packed into a minimum-cost set of bins, where each item $i, (1 \leq i \leq n)$, has a weight w_i. The binary variable x_{ij} is used to denote an item i packed into bin j and the binary variable y_j is used to indicate whether a bin j is used. Therefore, the objective function is to minimise the cost of the bins used for packing the items:

$$\min \left[\sum_{j \in J} c_j y_j \right] \tag{1}$$

with constraints that each item must be packed into one bin:

$$\sum_{j \in J} x_{ij} = 1, \;\; i \in I \tag{2}$$

and the total weight of all items loaded into a bin must not exceed the capacity of the bin:

$$\sum_{i \in I} w_i x_{ij} \leq b_j y_{ij}, \;\; j \in J \tag{3}$$

The bin packing task in this study consisted of a set of coloured blocks of different heights that needed to be packed into bins of various capacities and costs. The aim of the decision-maker was to pack all the items into bins for the minimum cost. To increase the cognitive demands placed on the decision-maker, the ratios of bin capacity to cost were non-monotonic so that both bin capacity and cost had to be considered. In addition, the smaller bins were designed to be too small to fit the larger items, thus further increasing the complexity of the problem.

The Augmented Reality Decision Support System (AR DSS). The aim of the AR DSS was *not* to provide the decision-makers with the solution to the bin packing problem; rather, it was to augment the scene with additional information that could be used by the decision-maker whilst completing the task. Therefore, the designs for the support mechanisms were based on the combination of two sources: optimisation-based online games, such as 'Fill the Fridge', and approaches for solving bin packing problems, such as the Best-Fit-Decreasing heuristic [12].

Fig. 1 shows the AR DSS in action. There are two augmented images projected above the task area. The left-hand projection is of the items that still need to be packed, with the heights of the items augmented onto their centres. The right-hand projection shows the bins and the blocks that have already been packed, with augmentations showing the remaining capacity in each used bin in addition to the item heights. Above the right-hand augmentation, the projection shows the current cost of the packed solution and the arithmetic breakdown of that cost (the cost of each used bin, from left to right). In addition to the AR projections, decision-makers could also see information sheets displaying the height of each item, and the cost and capacity of each bin (not in view in Fig. 1.)

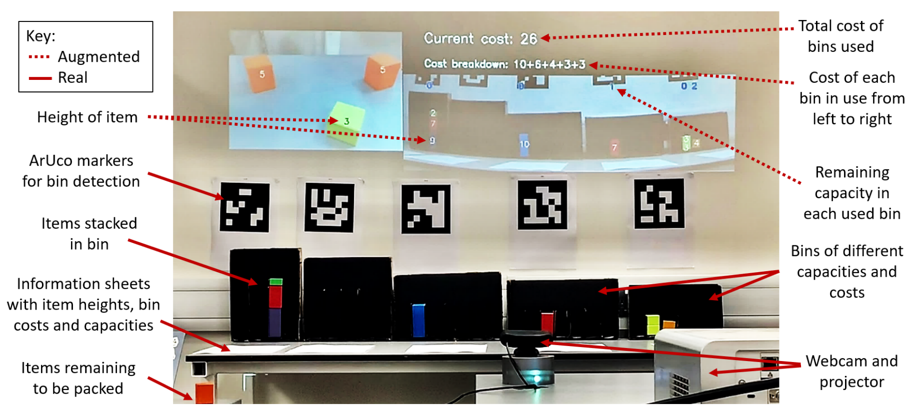

Fig. 1. Annotated image of the augmented reality decision support system (AR DSS) in action. The left-hand projection shows the remaining blocks to be packed, and the right-hand projection shows the bins with the blocks already packed into them. The control condition (without the AR DSS) was identical except for the removal of the item heights and excess capacity information from the projections (however, the current cost and cost calculation were still shown).

The augmentations were created using OpenCV, an open source software library for computer vision applications. The blocks were detected using HSVbased colour thresholding and the positions of the bins were detected using ArUco markers.

2.2 Experiment Design

A within-subjects experiment was conducted with an experimental group of 14 participants to compare completion of the bin packing task in two conditions: the intervention condition involving the AR DSS (item heights and remaining capacity augmented onto the scene) and the control condition (no item heights or remaining capacity augmentations). Each participant completed a packing task twice, once with the control condition and once with the intervention condition.

The order that the participants experienced the control/intervention conditions was randomised, with an equal split in which condition they experienced first. Participants were counterbalanced because learning effects were expected to influence task performance. To mitigate the learning effects from completing the first task session, the participants packed a different set of items in each packing task (known as Task A and Task B, each consisting of 12 different blocks to pack). The order that the participants experienced Task A and Task B was also randomised. Therefore, there were four sub-groups of participants in the study according to the conditions during their first task session (Task A/B, control/intervention).

2.3 Data Collection

Qualitative data was collected through semi-structured interviews to investigate the effect of the AR DSS on perceptions of the ease of the task. Two methods of qualitative data collection were used for each participant: observations during the packing tasks, followed by a semi-structured interview. Observations included the apparent strategy that participants were using, the frequency at which individual blocks were removed and repacked into bins, and any statements made by the participant whilst they were completing the tasks. The semi-structured interview was designed to collect thoughts and attitudes of participants about the packing tasks and AR DSS. This approach was chosen over a questionnaire to provide depth to participant's answers and explore issues with the DSS design and requirements for future design iterations. Therefore, participants were asked to elaborate (where appropriate) on the following questions:

1. What is the highest level at which you have studied a maths-based subject?
2. Do you have any experience completing optimisation problems, such as playing games that involve optimisation, or solving decision problems like the knapsack problem or travelling salesperson problem?
3. Have you ever used a virtual or augmented reality headset?
4. Did you find the task challenging to complete?
5. Please describe your thought process or tactics for completing the task.
6. Did you find the augmented reality tips useful in completing the task?

7. How did the task with augmented reality compare to the task without augmented reality?
8. What (if anything) would you change about the task?
9. What (if anything) would you change about the augmented reality tips?

Quantitative data was collected to investigate the effect of the AR DSS on the performance of decision-makers in the task. Participant performance was measured by recording the cost of their packing solution after a 3-minute time limit. Two costs were recorded for each participant, one with the control condition and one with the AR DSS intervention. To enable comparison between task sessions, the recorded cost for each session was transformed into *excess cost* by normalising it against the optimum packing cost:

$$excess\ cost = \frac{recorded\ cost}{optimum\ cost} - 1 \tag{4}$$

Therefore, an excess cost of 0 occurred when the recorded packing solution for the participant had the same cost as the optimum solution. An excess cost of 0 represented optimum performance of the participant.

2.4 Data Analysis

Qualitative data analysis was performed on the responses to the semi-structured interview and observed remarks made by participants whilst they were completing the packing task. Corbin and Strauss' approach to content analysis was followed to analyse the data [3]. Open coding was performed to identify interesting phenomena in the data and assign them a code. In-vivo coding (coding categories generated from phrases in the data) ensured that concepts remained similar to participants' own words. Researcher-denoted concepts were used to describe instances in the data that could not be described directly by phrases in the data. Subsequently, codes that described similar contents were grouped together to form concepts. Relationships between the concepts were identified using axial coding to form categories. Finally, the connections between concepts and categories were used to create inferential and predictive statements about the phenomena emerging from the data.

Quantitative data analysis was performed in SPSS, a statistical software platform, to investigate the effect of the AR DSS on the performance of decision-makers in the task. The Wilcoxon signed-ranks test was performed to assess whether differences between the excess cost distributions with and without the AR DSS were statistically significant. This test was chosen because the data violated the assumption of normality (non-parametric) required for a within-samples t-test. In addition, descriptive analytics were used to compare how the performance of participants changed between task session 1 and task session 2 depending on the order in which participants experienced the intervention and control conditions.

2.5 Study Participants

Recruitment Method. Participants were recruited in a non-randomised way based on ease of access, known as a convenience sample. Resource constraints limited the data collection period to four days, so convenience was vital to recruiting participants within the time frame.

Recruitment Setting. 13 out of 14 participants were postgraduate students, 9 of which were in maths-based subjects. Therefore, the results of the study are unlikely to be generalisable to the wider population.

Inclusion and Exclusion Criteria. Participants had to be capable of giving informed consent, any gender, aged 18 or over, any ethnicity, and any socioeconomic group. Participants could not take part in the study if they were visually impaired.

Ethical Considerations. The project was granted favourable ethical opinion by a University Research Ethics Committee (Ethics reference UoL2022_9560) based on an application form and supporting documentation submitted through the Lincoln Ethics Application System (LEAS). Written consent was given by all research study participants after they had read the participant information form and been given the opportunity to have any questions answered.

Compensation. Participants did not receive an payments, reimbursements of expenses, or incentives for taking part in this research. The participants were in the research facility for 30 minutes in total.

Gender. Out of 14 participants, 9 identified as cisgender men and 5 identified as cisgender women.

2.6 Methodological Limitations

Materials. This study used projection-based AR, so the results may differ to other forms of AR, particularly those using head-mounted displays. In addition, some flickering of the augmentations occurred due to the influence of participants' positioning on lighting and camera-view. This raises interesting questions about the influence of trust in, and reliability of, augmentations in decision support systems. However, these questions are outside the scope of this study.

Experiment Design. The data for each participant in the study was collected at one point in time (cross-sectional). Collecting data at multiple points in time (longitudinal) could mitigate the learning effects from completing the first bin packing task session.

Data Collection. Cognitive load was not measured directly, but was inferred from participant interview responses. Future work could measure perceived cognitive load using the Paas mental effort scale [24], a self-assessed cognitive load scale, as used in [2]. Alternatively, objective measures of cognitive load could be explored, such as pupil dilation [11].

Data Analysis. Conceptualising the qualitative data was done systematically to mitigate influence from preconceived opinions. However, the codes and concepts were products of researcher interpretation, so may be susceptible to biases.

8 out of 14 participants experienced Task A in the first task session. During quantitative data analysis, variation between Task A and Task B was assumed to have minimal impact on participant performance. This assumption was verified by comparing mean excess cost across both task sessions for participants based on whether they experienced Task A or Task B in the first task session [Task A first: mean excess cost 0.1119, standard deviation 0.0557; Task B first: mean excess cost 0.0991, standard deviation 0.0556]. An alternative research method could involve using a separate control group to record baseline performances for each task.

Study Participants The majority of the participants were postgraduate students with high maths ability, so the results of the study may not generalise to the wider population. Future studies would benefit from recruiting a larger number of participants from a wider pool.

3 Results and Discussion

3.1 The Effect of the AR DSS on Decision-Makers' Perceptions of Ease of the Task

The effect of the AR DSS on decision-makers' perceptions of ease of the task was investigated by performing content analysis on participant responses from semi-structured interviews and remarks that were observed whilst participants completed the packing task.

Results. Participant responses were separated into two broad categories based on taxonomies of human capabilities from the fields of psychology and Human-Computer Interaction [17, 6]. The first category, *cognitive*, was used to group participants' responses relating to "reasoning, thinking and one's ability to solve problems in novel situations independent of acquired knowledge" [10]. The second category, *perceptual*, consisted of participant responses relating to their sensed environment through sensory organs, such as vision, hearing and touch [30]. The code structure that emerged from analysing the participant responses is shown in Fig. 2.

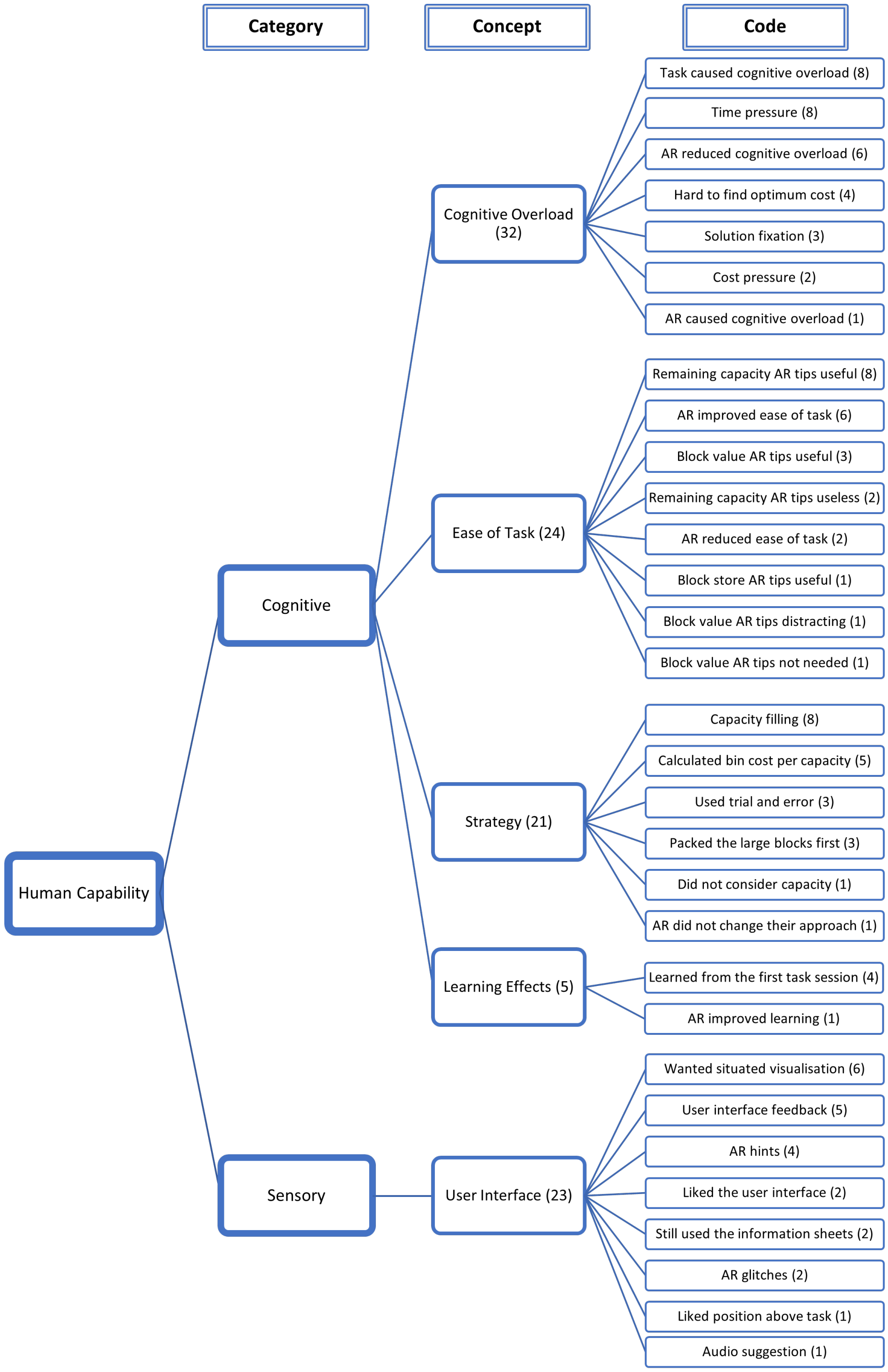

Fig. 2. An image showing the code structure that emerged during analysis of participants' responses to questions in a semi-structured interview and remarks made during the bin packing exercises. The numbers in brackets at the code level represent the number of participants that expressed a sentiment relating to the code. The numbers in brackets at the concept level are the totals of the brackets in the code category – some participants mentioned different aspects (codes) of the same concept, hence why the numbers are greater than the total number of participants (14).

The main objective of collecting qualitative data was to investigate the effect of the AR DSS on how easy or difficult participants perceived the packing task to be. Under the 'Ease of Task' concept, 6 participants expressed that AR improved the ease of the task, 8 participants stated that the remaining bin capacity AR tips were useful, 3 participants described the AR block values overlaid onto the blocks as useful, and 1 participant highlighted that the values on the blocks were particularly useful in the unpacked items area. For example, one participant (ID 09) stated that AR made the task "easier to solve because [they] could see what the remaining capacity in the bins was much faster when they experimented and see better combinations of blocks when they were still in the block store". Another participant (ID 11) stated that the "packing was easier with AR because [they] could see how much [they] needed to pack without having to work it out". However, not all comments related to 'Ease of Task' were positive. 2 participants stated that they did not use the remaining capacity AR tips and 1 participant expressed that the block values overlaid onto the blocks were not necessary. Furthermore, 2 participants indicated that the AR DSS reduced the ease of the task and 1 participant stated that the AR block values were distracting. This was because the "AR values on the blocks drew attention away from the remaining capacity" (ID 08). Overall, there were more comments from participants indicating that the AR DSS made the task easier (18) than comments that were impartial (3) or negative (3).

In addition to discussing their perceptions about the ease of the task, some participants commented on their mental operations directly, with phrases such as "mental maths" (ID 13) and "mentally calculating" (ID 14). Others referred to the cognitive load they were experiencing, with phrases such as "mental load" (ID 02) and "mental capacity" (ID 12). 8 participants indicated that the task itself caused cognitive overload. For example, one participant (ID 10) stated that there was "a lot going on so there [was] too much to keep track of easily". Another participant (ID 12) expressed that they "didn't have the mental capacity to compute the costs [of the bins used]". This was in part due to the time pressure of the task session, as mentioned by 8 participants. One such participant (ID 11) explained that the task was "challenging because there was a time limit, so stress got in the way". 6 participants suggested that the AR DSS reduced the cognitive load of the task. For example, one such participant (ID 05) said that their "thought processes were quicker with AR because [they] didn't have to calculate how full the bins were". However, 1 participant (ID 08) explained that the AR DSS increased feelings of cognitive overload, saying "if I was a numbers person it would have been useful but for me, when I looked at the item size and saw all the other numbers, it was confusing".

Some participants also provided feedback on the user interface of the AR DSS. The most frequent comment (6 participants) concerned situated visualisation, whereby they indicated that the DSS may have been more effective if the AR tips were projected directly onto the real blocks. For example, one participant (ID 13) said that the DSS would be better if they "didn't have to look down and up". They elaborated that they were dissuaded from using the AR DSS because "looking between real and augmented took too much concentration".

Discussion. Content analysis indicates that the AR DSS had a positive effect on the decision-makers' perceptions of ease of the task. In total, there were 18 comments from participants indicating that the AR DSS made the task easier, 3 impartial comments and 3 negative. This aligns with previous studies reporting that AR improves perception and understanding of information in situations where decision-makers have to refer to external sources of information, such as monitor- or paper-based information [14].

A possible explanation for the improvement in perceived ease of the task with the AR DSS is that it reduced the cognitive load of participants. Cognitive Load Theory proposes three types of cognitive load: intrinsic (imposed by the task itself), extraneous (imposed by the presentation of task information), and germane (reflective of the effort required to generate mental schemas in the working memory and store them in the long-term memory) [33]. 8 participants indicated that intrinsic cognitive load was present through comments about the difficulty of the task. It has been suggested that presenting information in the context that it is required reduces extraneous load, enabling more cognitive resources to be focused on the generation of schemas, problem-solving, or task completion [14]. This aligns with the DSS literature, which suggests that AR could help to alleviate load on the working memory by acting as an "external memory" through provision of relevant and appropriate information to decision-makers [4, 23, 29]. Therefore, the use of AR to augment the task environment with information may have reduced extraneous cognitive load, thus resulting in increased perceptions of ease by participants.

It has been suggested that AR may reduce cognitive load because it "negates the need to switch between performing the task and searching for information to perform the task" [14]. 6 participants discussed situated visualisation and indicated that the AR DSS may have been more effective if the augmentations were projected directly onto the real blocks. This could further alleviate the need to cognitively map information from the projection to the real objects [26].

3.2 The Effect of the AR DSS on Task Performance

The performance of decision-makers was measured by the *excess cost* of their packing solution compared to the optimum, as given in Eq. 4. The lower the excess cost, the better the performance – an excess cost of 0 is the best achievable performance in the task.

Results. The performances of participants with and without the AR DSS are shown in the boxplots in Fig. 3, where a lower excess cost denotes a better performance. In the AR DSS condition, the participants' mean excess cost was 0.0969, the median was 0.0870, and the standard deviation was 0.06841. In the control condition, the participants had a higher excess cost mean of 0.1159, a higher median of 0.0882, and a higher standard deviation of 0.09498. The difference in means suggest that the performance of participants was better by 16.4% with the AR DSS compared to without, indicated by a decrease in excess cost above the optimum solution. In addition, the spread of the data is smaller, indicating that there was less variation in performance between participants when the AR DSS was present.

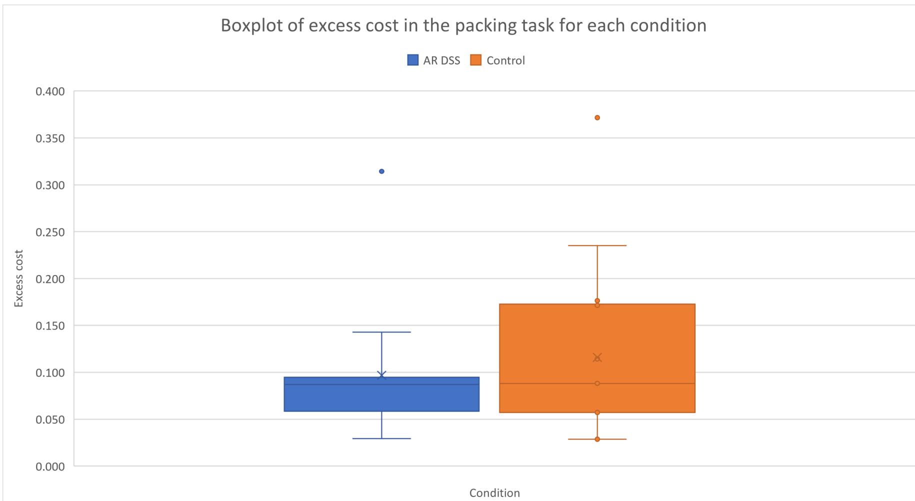

Fig. 3. An image showing boxplots of the excess cost of participants' bin packing solutions under each condition. A lower excess cost represents a better performance.

The distribution of data points for excess cost in the presence of the AR DSS departed significantly from normality (Shapiro-Wilk test for normality: $W(14) = 0.666, p < 0.001$). Therefore, the non-parametric Wilcoxon signed-ranks test was used to measure the effect of the AR DSS on the performance of decision-makers. 5 participants had a higher excess cost (worse performance) in the AR DSS condition and 9 participants had a higher excess cost in the control condition. Therefore, more participants performed better with the AR DSS than without the AR DSS. Nevertheless, the Wilcoxon signed-ranks test showed that the AR DSS did not elicit a statistically significant change in performance, as measured by excess cost compared to the optimum $(Z = -0.628, p = 0.530)$. Indeed, median excess cost was 0.0870 with the AR DSS compared to 0.0882 without the AR DSS. As a result, the null hypothesis that there was no significant difference between the excess cost with and without the AR DSS cannot be rejected.

The participants were counterbalanced to experience either the AR DSS or control condition first. However, analysing the data by task session in addition to intervention/control condition suggests that there is a relationship between them, as shown in Fig. 4. The participants that experienced the AR DSS condition in the first task session performed better in both conditions than those that experienced the control condition in the first task session. Mean participant performance improved between the first and second task session regardless of the order that conditions were experienced. However, performance improvement between the first and second task session was greater when the participant moved from the control condition in the first task session to the AR DSS condition in the second task session (compared to moving from the AR DSS condition to the control condition).

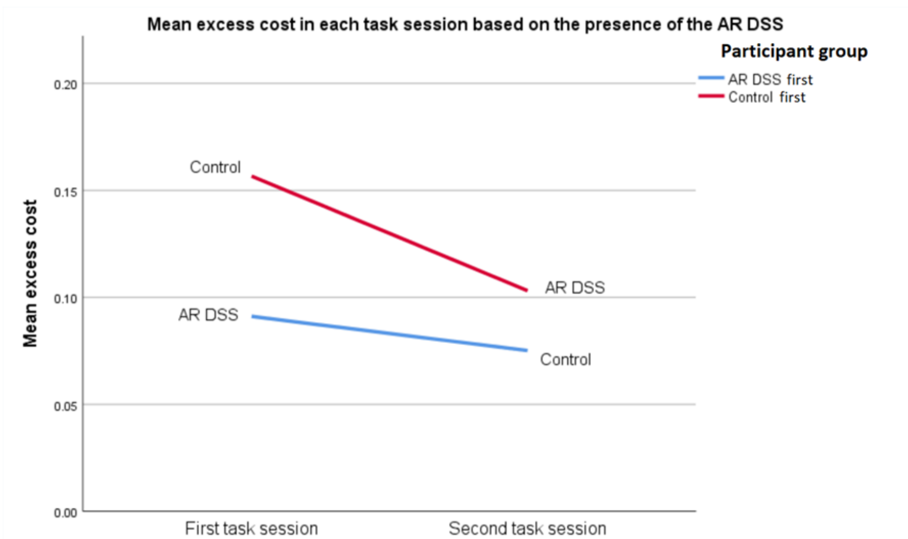

Fig. 4. The mean excess cost of participants in each task session separated based on whether the AR condition was experienced in the first or second task session. A lower excess cost indicates a better performance.

Discussion. The data indicates higher performance for participants when the AR DSS was present compared to when it was not; however, the difference in performance is not statistically significant. On average, participants that experienced the AR DSS in the first task session had a higher performance across both sessions. This finding implies that the use of AR could accelerate learning of approaches to solve novel problems. Furthermore, the amplified learning effects between the first and second task sessions when moving from the control condition to the AR condition suggest that the AR DSS improved learning above that of prior task experience alone. However, these findings were not anticipated, so the experiment was not designed to investigate learning effects specifically.

3.3 The Relationship Between Perception of Ease and Task Performance

Results. The aggregate data suggests that both perceived ease and task performance increase in the presence of the AR DSS; although, the increase in performance is not statistically significant. However, at the individual level, there is no correlation between change in perception of ease and change in performance. For each individual participant, Fig. 5 shows the perceived ease of the task with the AR DSS compared to without, plotted against the difference in performance between the task with the AR DSS and without. The x-axis represents the sentiments of each participant about the relative ease of the task under each condition. The three categories are researcher-denoted based on the interview content analysis, with each participant indicating either a positive, a negative or no change in perceived ease of the task. The y-axis displays the difference in task performance for each participant, calculated by subtracting the excess cost with the AR DSS from the excess cost without the AR DSS. The plot indicates that at the individual level there is no relationship between perceived ease of the task and performance in the task.

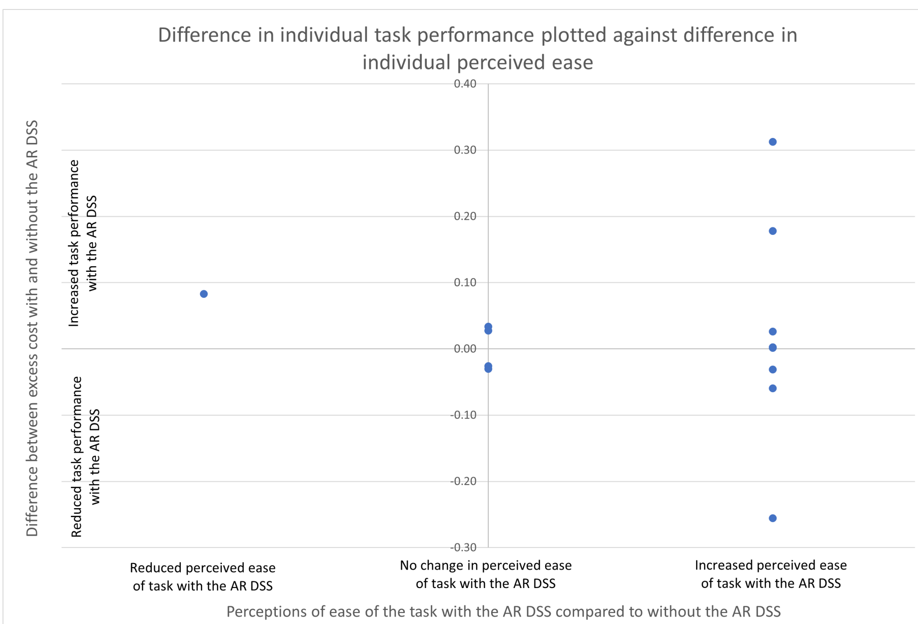

Fig. 5. The difference in task performance between the AR DSS and control condition plotted against the perceived ease of the task with the AR DSS compared to without.

Discussion. Previous findings suggest that improvements to task performance may result from AR freeing up mental resources such as the working memory, thus reducing cognitive load [14]. However, this study has been unable to demonstrate a relationship at the individual level between changes in perceived ease of the task and changes in task performance. A possible explanation for this is that participants' perceptions about the ease of the task do not correspond to their cognitive load. Alternatively, there may be factors other than cognitive load that affect perceptions about ease of the task and mean task performance. For example, studies investigating AR to provide instructions in assembly tasks suggest that AR could change the type of cognitive demands placed on the user [5], or introduce an additional source of attentional demand, resulting in attentional tunneling [34].

4 Conclusions

This paper aimed to contribute to the field of augmented cognition by conducting an exploratory study to investigate the effects of AR on cognitive load during operational decision-making.

An augmented reality decision support system (AR DSS) was developed to assist decision-making whilst participants completed a variable-sized bin packing task. The AR DSS used computer vision techniques to overlay information onto a projection of the scene. This included overlaying the size of the blocks onto their centres and displaying the remaining capacity over each bin in use. The overlaid information was designed to augment the decision-making process, not to provide instructions or solutions to the decision-maker.

The research study used a within-subjects experiment, collecting both qualitative and quantitative data. 14 participants completed two bin packing tasks, one with the AR DSS (intervention condition) and one without (control condition). The order that participants experienced the conditions was counterbalanced to account for learning effects between the task sessions. The primary research aim was to explore the effects of AR on the cognitive load of decision-makers. This was done by investigating the effects of the AR DSS on decision-makers' perceptions of the ease of completing a bin packing task. Participant perceptions were elicited by conducting semi-structured interviews. A secondary research aim was to investigate the link between changes in perceived ease of the task and changes in task performance. Participant performance was measured as a ratio of the cost of the participant's solution in the packing task compared to the optimum solution.

The qualitative data suggests that, more often than not, the presence of the AR DSS made the task feel easier to participants. This could be because it alleviated the load on the working memory by serving as an "external memory" [23], thus reducing extraneous cognitive load. The quantitative data does not indicate a statistically significant increase in task performance with the presence of the AR DSS. However, it does appear conducive to participants learning how to solve novel tasks. At the aggregate level, the collected data is insufficient to derive a relationship between perceived ease and task performance. Analysing the data at the individual level does not provide evidence of a translation of increased perceived ease to increased task performance. A possible explanation for this is that participants' perceptions about the ease of the task do not correspond to their cognitive load. Alternatively, there may be factors other than cognitive load that affect perceptions about ease of the task and mean task performance. For example, AR could change the type of cognitive demands placed on the user [5], or introduce an additional source of attentional demand, resulting in attentional tunneling [34].

4.1 Future Work

The findings from this study indicate that the presence of AR may impact the learning effects observed between task sessions 1 and 2. However, these findings were not anticipated. Future work could specifically investigate the learning effects of AR by asking participants to complete the first and second task sessions solely with either the AR DSS or control condition.

In addition, this project looked at projection-based augmented reality; however, 6 participants expressed that the DSS may have been more effective if the information were situated directly on the task. This could be explored in future work using an AR head-mounted display.

Suggestions for possible changes to research methodology in future work include:

- Increase the number of participants in the study to achieve statistically significant results.
- Use a wider participant pool to obtain results that are more applicable to the wider population.
- Perform a longitudinal study to minimise the learning effects of completing two bin packing task sessions.
- Obtain baseline performances for each task using a separate control group of participants.
- Use multiple coders for qualitative data analysis and check reliability of the coding using metrics such as Cohen's Kappa.

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