A Probabilistic Approach to Understanding User Preferences for Adaptive Placement of AR Interfaces in Different Physical Environments

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Abstract—We develop a probabilistic approach to understanding user preferences for adaptive placement of augmented reality (AR) interfaces in the physical environment through a series of user studies conducted using simulated desktop and virtual reality (VR) environments. From the first online crowdsourcing study and its validation in VR, we derived a set of potential factors behind user preferences for AR interface adaptation by assessing user-created layouts and analysing subjective user feedback. Building on this prior knowledge, we implemented a probabilistic optimisation system to generate adapted AR interfaces. Using generated layout pairs that prioritise different factors, we conducted a second online crowdsourcing study (N = 250) to elicit user preference rating data to quantify posterior probabilities for the weighting coefficients of the factors in the optimisation utility function. Overall, we found that the overall structures of layouts, such as shape and distribution, are more important to users than adapting to specific features of the environment, such as semantic associations between AR widgets and objects in the physical environments. We contribute a statistical model containing probabilistic distributions of different factors as a universal prior model that represents user preferences for AR interface placement that adapts to changing physical environments. Based on the results, we distil concrete guidelines for future adaptive AR interface systems regarding layout consistency, structure, and relationships between virtual widgets and physical objects.

Index Terms—Extended reality; augmented reality; adaptive interface

1 Introduction

The advancement of augmented reality (AR) technologies promises a future in which we see and use digital workspaces for daily tasks through a pair of glasses, such as Apple Vision Pro and Meta Quest 3 that are capable of integrating the digital content with the physical environment, instead of desktop and mobile screens. Whereas most of us are skilled in navigating a screen, the same task may not be so easy in AR. Imagine turning on your AR headset in a new physical environment: while your nicely arranged "home screen" appears in front of your eyes, you may find the weather widget blocking the TV that you were watching or the social media window appearing next to the paper that you have been struggling to read. While current AR headsets still feature large and flat window-based interfaces, future AR devices would benefit from automatically rendering users' personal interface consisted of multiple individual windows and widgets. The layout of these UI elements can adapt to the egocentric space, helping users locate and interact with frequently-used applications without hindering activities in the physical environment.

The challenge in designing successful adaptive AR interfaces is twofold: to disentangle the influence of multiple factors on user preference for the placement of the interface layout in the physical environment and to meet their diverse objectives of using AR. For example, previous research has proposed adaptive AR interfaces focusing on a range of factors, including environment geometry [11], environment semantics [30], task [3], and users' mental states [29]. Whereas these works proposed novel algorithms or methods with different foci, it is challenging to determine which factors are more important than others, or how these factors that have been explored in separate studies would interact with each other. Moreover, some of these factors assumed contextual knowledge beyond the capabilities of the AR headsets, such as the task that the user planned to perform. Those assumptions limit generalisability of the proposed systems to broader scenarios where there is limited contextual information. The predictably large variance in individual interpretation of different task scenarios and different habitual uses of software tools also make it difficult to predict user expectations for adaptive placement of AR interfaces based on those factors [55], or to evaluate adaptive systems (that aim to account for these factors) by enumerating different contextual changes that may affect the adaptation outcome [40]. To explore these more advanced features of adaptive AR interface, we first need the basic understanding of how users would like their personal AR workspace to adapt only to the change of physical environment by isolating its effect. Such knowledge can inform us with user preferences for layout adaptation that are not influenced by other contextual information, such as task or intention, while providing a basis that such explorations need to build on. In this paper, we fill this gap and address the challenges in adaptive AR interface through two research questions: RQ1: What are the factors that impact user preference for adaptive placement of AR interface layouts? RQ2: How can we quantify the relative importance of these factors based on a large sample of users?

To address these questions, we conducted a series of studies aiming to build a probabilistic model for adapting a user-created default AR interface layout only using contextual information that is available in the physical environment without assuming user-specific goals. Using simulated desktop and VR environments, we adopted a crowdsourcing method to achieve a reliable prediction of the relative importance of a set of factors representing universal user preference from a large sample. Through an online crowdsourcing study and its validation in VR, we learned how users manually created and adapted their interface around their bodies based on quantitative modelling, and learned user preferences between fundamental adaptive placement strategies. Based on this knowledge, we implemented an optimisation system to simulate user outputs of adaptive layout placement. Using 8001 pairs

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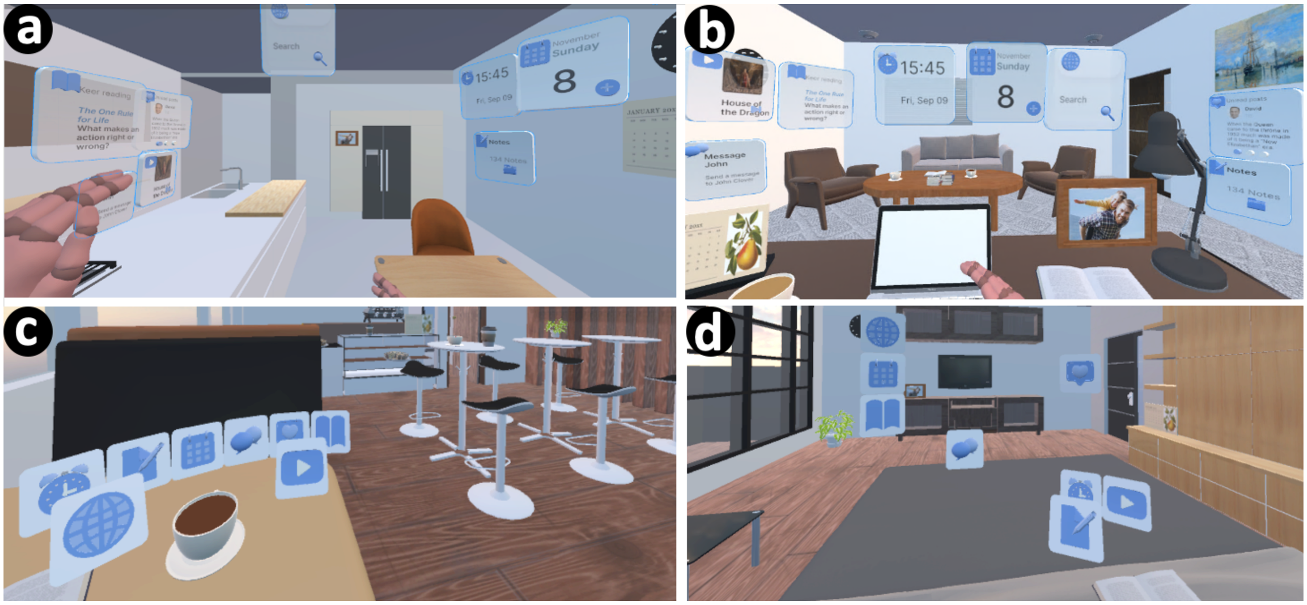

Fig. 1: Example user-created and system-generated AR interfaces adapted for the four environments. In Study 1 and 2, after creating a default layout in a featureless environment, participants were moved through "a work day in AR": in which they (a) prepared for the day in the kitchen in the morning, (b) worked in the office during the day, (c) relaxed in a cafe in the evening, and (d) rested in bed at night. Participants manually created and adapted layouts in Study 1 and 2, and selected their preferences from pairs of layouts created using an optimisation system in Study 3. The example layouts in (a) and (b) were created by a participant by adjusting widget locations in a default layout that was copied into the working environment during Study 1. The layouts in (c) and (d) were generated for eliciting user preference data in Study 3 using an optimisation system that generates adapted layouts while prioritising different factors representing different widget placement strategies, based on empirical findings from the first two studies.

of 127 unique layouts generated by our system, we conducted a second online crowdsourcing study to elicit user preference data that yielded a set of probability distributions of the effect of different factors that predict user preference for adapted layouts. Through these studies, we address the gap in the literature by contributing the first empirical understanding of how different AR interface layout adaptation strategies and factors predict user preference by quantifying their impact through probabilistic modelling of data collected from a large sample. Specifically, we designed our data collection method to elicit user preferences for AR interface layout adaptation that reacts to changes in physical environments while minimising the influence of individual variance in assumptions related to other use contexts. Based on the results, we distil concrete guidelines for future adaptive AR interface placement systems. Finally, we open-source the probabilistic model and data for reproducibility and future extensions.

The remainder of this paper reviews related work (Section 2), introduces our overall method (Section 3), reports (Section 4- 5) and discusses (Section 6) the design and results from the first online crowdsourcing study and its VR validation, documents the optimisation system (Section 7) and the final preference elicitation study (Section 8), discusses the final results (Section 9) and future work (Section 10), and summarises the conclusions and contributions (Section 11).

2 Related Work

We summarise the findings from previous work on AR interface adaptation. We found that though environment-specific factors are important, there is still a lack of an empirical understanding of the relative importance of different factors. In particular, little attention has been paid to factors related to users' perception and use of the space around their bodies, such as spatial memory, visual clutter, and the spatial distribution of widgets in the egocentric reference frame of the user.

2.1 View Management for AR Interfaces

Since the early days of AR, authors have explored its potential to expand digital interfaces, thanks to the capability of rendering virtual content directly over the physical environment. Feiner proposed the first AR prototype that rendered 2D windows on the 3D physical environment following different approaches for anchoring the windows, including view-anchored, object-anchored, and world-anchored [15]. It raised the issue of visual clutter and occlusion between AR content and objects in the physical environment. Subsequently, the same authors proposed a view management system in AR that arranged virtual annotations unobtrusively [2]. With progress in hardware and software, more research works have subsequently explored view management methods for personal AR interfaces. For instance, McGill et al. explored how large 2D windows surrounding the user could be navigated using implicit control with gaze and head tracking [37]. Lu et al. [31, 32] focused on users' peripheral vision and explored approaches for expanding AR interfaces by displaying AR content in their peripheral vision. They proposed "Glanceable AR" to enable users to access AR applications by glancing while avoiding visual clutter and occlusion [31, 32].

Apart from occlusion, the proper arrangement of an AR interface between users and their surrounding environments is also important to its efficiency. Previous work found that the effective use of landmarks, such as layouts, edges, and corners, supports spatial memory of commands in 2D graphical interfaces [46]. While the same benefit of spatial memory is equally important to AR interfaces, the problem could be further complicated by the third dimension over 2D UIs and by the virtual content directly augmenting objects in the physical environment. Cockburn et al. investigated this impact, finding that the third (depth) dimension makes it more challenging for users to benefit from the spatial memory of an interface compared to 2D interfaces, partly due to the visual cluttering [7]. Similarly, Tatzgern et al. found a benefit in reducing the clutter of virtual information over the physical environment in AR [51]. These findings suggest that the usability of personal AR interface layouts can benefit from better spatial memory afforded by better-defined structures with consistent depths between their components while not obstructing each other or users' views on the physical environment [27, 34, 48, 49, 58]. While previous findings have suggested different benefits of how the view of personal AR interfaces may be arranged, there is a conflict between defining better structures of the interface layout and adapting it to accommodate the physical environment while avoiding visual clutter and occlusion. Further, previous evidence accumulated in a 2D desktop context may not extend in 3D contexts in AR with the added complexity of the physical environment. We contribute empirical evidence to address this conflict through investigating how the potential effects of the spatial consistency and structures of adaptive AR interface layouts and of the visibility of the physical environment may impact user preferences.

2.2 Egocentric Arrangement of AR Interfaces

The mobility afforded by AR headsets means that content must adapt to unpredictable changes in the physical environment around them. However, the user's body remains a constant reference frame for rendering and arranging the AR interface in the egocentric space. Many previous works have envisioned different uses of this space while benefiting from sensing technologies typically found in AR devices. For instance, Gustafson et al. proposed *Imaginary Interfaces* that enable gestural interaction without visual feedback while relying on users' spatial perception of their egocentric space [22]. Wagner et al. described *Body Scape*, a design space of interaction on and around different parts of the body [53]. Other works explored accessing virtual objects in the egocentric space purely relying on bodily senses without visual access [56,59]. These works demonstrated a vision of expanding the interaction affordances of the egocentric space around the body to enable ubiquitous interaction on the move.

Other works have explored possible display technologies in the egocentric space. For instance, Grubert et al. evaluated multi-fidelity interfaces on and around the body to expand the display space of small-screen devices [20]. Chen et al. proposed techniques for extending mobile devices' interaction spaces by enabling unbounded scrolling while moving the screen around the body [5]. With AR headsets, Ens et al. explored a similar approach in a series of works, such as *Ethereal Planes* [10] and *Personal Cockpit* [12]. They contributed novel interaction techniques that enable multi-tasking with multiple application windows in AR while sidestepping the limit of the FoV. Similarly, *XR-gonomics* investigated the suitable locations for placing AR content in the egocentric space for direct manual interaction in greater detail [13]. However, these works are mainly concerned with the use of the egocentric space, either without realistic use contexts, or with specific foci, such as multi-tasking, ergonomics, and extending the FoV. To effectively integrate these knowledge of egocentric arrangement of interface elements in the context of adaptive AR interface layout, we need to understand how these factors interact with other factors concerning the broader context of use, including visual occlusion and semantic meanings of physical objects in view. Building upon previous findings, we model angular and distance distributions of widget locations in AR interface layouts that are created and adapted in the egocentric space relative to the user's body. Further, we integrate these distributions as prior knowledge for simulating user outputs, and for contributing a probabilistic model of user preference for adaptive AR interface based on empirical data obtained in a simulated realistic use context.

2.3 Adaptive AR interfaces

Benefiting from advanced sensing technologies, research works have explored possibilities of automatically adapting room-scale 3D MR interface layouts according to the physical environment. Pick et al. proposed a method to render annotations that adapt to different geometry of the walls in a CAVE environment [43]. *HeatSpace* captures the environment and the user in 3D and adapts the locations for rendering virtual content to the geometric features of the room to optimise visibility [16]. Similarly, *SpaceState* reacts to changes in the physical layout of a room and enables designers to interactively define its global and local states [17]. *Retargetable AR* provides more specific semantic descriptions of physical rooms for AR content placement, such as "TV in front of chair" [50]. Works like this do not only adapt the layout of virtual content based on environment *geometry* but also on its *semantic* structure. Other works explored methods reacting to context changes induced by users' walking [26, 33].

Apart from features of the physical environment, previous works also investigated AR layout adaptation methods, focusing on other factors, such as the task at hand and the consistency of the spatial layout of the interface. Bonanni et al. proposed a framework for designing task-oriented AR interfaces that accommodate the spatial and temporal qualities of the task and the location of the user [3]. Other works focused on maintaining the temporal-spatial constancy of AR content to aid users' spatial memory and retrieval [35]. For instance, Ens et al. adapted surface-embedded AR layouts across different environments while maintaining constancy between application windows [11].

In recent years, a series of AR personal interface adaptation algorithms have been proposed, typically following computational approaches such as combinatorial optimisation [39]. These approaches have also been applied in 2D interface optimisation problems [9]. For instance, *AUIT* facilitates the design of optimisation-based adaptation policies by allowing designers to flexibly incorporate factors such as visibility, layout consistency, etc. [14]. *ScalAR* enables designers to author semantically adaptive AR experiences in VR [44]. Among these works, Lindlbauer et al. contributed a series of optimisation-based algorithms while considering multiple factors. These include an online adaptation method of MR interfaces combining the external room state and the internal mental state of the users [29], and Cheng et al.'s *SemanticAdapt* [6] that focused on the semantic associations between AR widgets and the physical environment. Reflecting on these works, Lindlbauer pointed to the importance of identifying the appropriate contextual information as factors of the algorithm while acknowledging the challenge in enumerating and accessing that information [28].

Though these works contributed algorithms, none of them provided a systematic empirical understanding of what contextual information users would prioritise in adaptive placement of AR interface layouts. Whereas environment integration and egocentric layout around the body have been found to improve user satisfaction in adaptive AR interfaces, it was scarcely understood which approach users would prefer in what scenarios or for what reason. In this work, we contribute an empirical understanding of user preferences and strategies for adaptive placement of AR personal interfaces across different environments to provide an empirical basis for future works. Inspired by the optimisation-based adaptation approaches, we employ an adaptation algorithm to simulate user output in layout placement adaptation for eliciting user preference data through online crowdsourcing.

3 Method

With this research, we aim to contribute a prior probabilistic model that predicts user preference for adaptive placement of AR interface layouts based on different factors regarding user expectations and strategies for using the immediate space around their body together with the external physical environment for AR. Specifically, we aim to address the following research questions: RQ1: What are the factors that impact user preference for adaptive placement of AR interface layouts? RQ2: How can we quantify the relative importance of these factors based on a large sample of users?

To this end, we explored whether using a desktop virtual environment can work as a cost-effective way of crowdsourcing users' interface adaptation strategies at scale. We collected data on how users place widgets in an AR interface and how they rate different pre-built layouts using an online crowdsourcing platform, then replicated the online study in VR and compared the results. Based on empirical findings, we implemented an optimisation algorithm to simulate user layout adaptive placement outputs and generated different adaptations of a default layout and shuffled them in pairs to elicit user preference data in a third online crowdsourcing study. The main procedures of all three studies are shown in Figure 2.

3.1 Scenario and Environments

We aimed to set a plausible context for participants to create and adapt AR interfaces in different environments. To this end, we created a context of one day in AR with the environments presented from morning to night. This context provides a convincing and consistent scenario to adapt the placement of the AR layout for. We carefully designed four environments to provide variances in geometries, such as the Office and Cafe environments with the presence of a Desk/Table, and the Kitchen/Bedroom environments featuring open space. We built the environments from popular assets in a common furniture-placement and

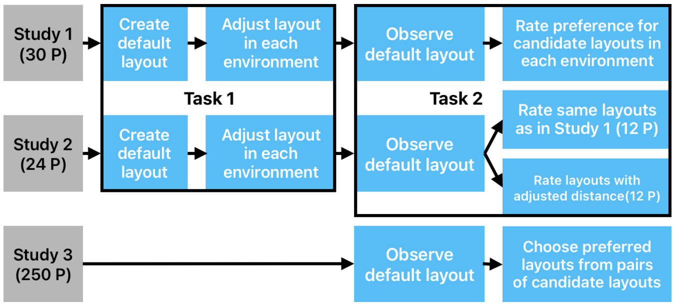

Fig. 2: Task procedures of Study 1 (crowdsourcing), Study 2 (VR lab study), and Study 3 (large sample crowdsourcing).

decoration style to enable intuitive understanding based on universal familiarity. We placed a series of physical objects in all environments, including a clock, a photo frame, a calendar, a book, etc., to create a realistic need of eliciting semantic associations with AR widgets.

We presented the environments with a scenario of "a workday in AR" with four environments to which they would travel during the day: a kitchen to get ready in the morning, an office to work during the day, a cafe to relax in the afternoon, and a bedroom to rest at night (Figure 1). We presented the environments in this order for all participants across all studies to give them a realistic context of environment changes to consider adapting for layouts for. To maximise the ecological validity of our results, we presented the environments to participants without further instructions regarding more specific tasks to alleviate the variance in different individual interpretations of them. Each environment is a $6m \times 6m$ room with different furniture, objects, and viewpoint locations. Previous work found that users may prefer placing widgets near objects they are semantically associated with [6]. To understand this potential strategy, we placed the same objects in each environment at different locations: clock, calendar, family picture, book, and beverage (Figure 1). Finally, we considered the case where the layout is rendered based only on contextual information captured from a static viewpoint without considering movement. The scenario and environments were used across all studies with minor adjustments.

3.2 AR Application Widgets

We designed eight widgets to be incorporated into the AR interface: browser, calendar, social media, messages, clock, document, note, and video player. We chose the widgets based on the most popular apps in mobile app stores according to data obtained from *Statista.com*. For each widget, we designed three different levels of detail (LoD) in three different sizes (small, medium, and large) containing different degrees of visual details of their contents and features to better accommodate users' preferences (Figure 3). We adopted this design choice based on findings from previous work that users may prefer different LoDs to suit the cognitive demand of the task at hand [29]. The LoDs help convey a more realistic use case scenario to elicit natural user behaviour in layout creation and rating in Study 1 and 2. For Study 3, while still showing participants close-up details of the different LoDs of all widgets to provide an understanding of their purpose and interactivity, we removed the variations in LoD for the system-generated layouts presented in the rating task, to reduce potential confounds in user preference elicitation, and to focus the probabilistic model on reflecting the effects of the factors. At the beginning of all three studies, we showed participants the details of all widgets in all LoDs. In Study 1 and 2, we asked participants to rate the perceived usefulness of each widget on a scale of zero (lowest usefulness) to ten (highest usefulness). We used the usefulness rating to help answer RQ1 and RQ2. This also allowed us to abstract from the particular applications and instead focus on how participants perceive them in our statistical modelling.

4 Study 1: Crowdsourcing Layout Adaptation & Rating

4.1 Task 1: Creating and Adapting AR Interface

To gain an understanding of where users would like to place AR interface widgets and how they would like the layouts of the interface to be adapted to a new physical environment, we asked participants to first create an AR interface layout in an empty room. At the beginning of Task 1, we showed the participants eight AR application widgets and asked them to rate their subjective perceived usefulness. Then, participants saw themselves in the centre of an empty room ($6m$ x $6m$) and were asked to create a default AR interface layout by placing all eight widgets individually at any location in the empty room. Before creating the layout, participants were notified that they would adapt this layout to other environments. Then, they were shown the four environments, where the same default layout is copied while maintaining spatial consistency relative to the avatar's head. Participants were instructed to adjust the widget locations and LoDs to adapt the interface to the new environment as much as they liked. Figure 1 (a-b) illustrates two layouts from such a sequence in Study 1.

4.1.1 Task 1 Procedure

We first provided textual and image instructions to introduce the purpose of the study and its tasks, followed by the usefulness rating scene. Once in the default layout creation scene, participants were able to load widgets from the menu bar on the top of the screen onto the scene using the number keys and subsequently perform translation, rotation, LoD switching, and perspective switching between first-person (1PP) and third-person perspective (3PP) using dedicated keys for each function. When each widget was first loaded, they were spawned directly in front of the user's face at a distance of 0.45 metres. This distance was based on MRTK's guidelines [38] to ensure widget font readability and general interaction comfort. After loading all eight scenes, participants were presented with the four environments with the option of moving any widget in the layout (Figure 4). Then, participants were presented with an empty room again and required to reconstruct the default layout they created at the beginning for attention screening. We excluded participant data if the reconstructed layout was too different from the default layout. We manually screened the data due to the difficulty in judging automatically because participants may have only remembered some parts or aspects of the default layout. We only excluded data when there was obviously no effort, e.g., if the reconstructed layout was linear whereas the original layout was structured into rows, or if the widgets were barely moved in the reconstructed layout.

4.2 Task 2: Preference for Candidate Layouts

With Task 2, we aimed to gain a preliminary understanding of user preferences for different basic adaptation strategies concerning the incorporation of the features of the environment in a controlled setting. In Task 2, we employed a 2×2 factorial design with two independent variables STRUCTURE and STRATEGIES to represent trade-offs in different strategies for adaptive placement of AR layouts. While STRUCTURE captures the environments' effects on the overall structures of the layouts, STRATEGIES captures the environments' effects on the relative locations of widgets within the layouts.

STRUCTURE has two levels: COMPACT and GEOMETRY. In COMPACT layouts, widgets are arranged tightly together while floating in front of the user's viewpoint. In GEOMETRY layouts, widgets are placed on environment surfaces that are close to the user's body, among the physical objects on them. STRATEGIES has two levels: CONSISTENT and SEMANTIC. We aimed to understand whether users would prefer the placement of AR widgets to be arranged while remaining CONSISTENT in their relative locations (to each other) with the default layout, or discarding their relative consistency and being moved individually close to environment objects that share SEMANTIC associations with them. Following combinations of these variables, we manually created four candidate layouts as adaptations of the default layout in each environment. As an example, we present the layout options in the office environment as examples in Figure 3.

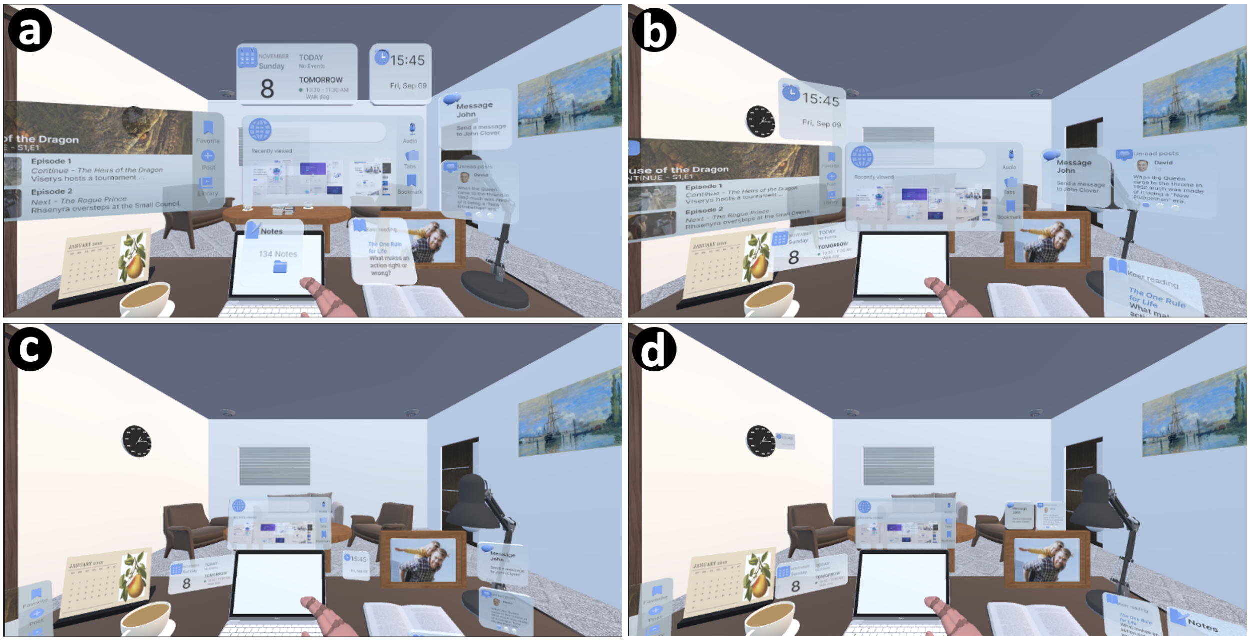

Fig. 3: (a) COMPACT x CONSISTENT: an exact copy of the pre-built default layout observed by participants previously in the featureless environment. The location of the layout relative to the viewpoint is the same as the default layout. (b) COMPACT x SEMANTIC: while maintaining a compact structure similar to the default layout, the widgets are moved close to objects that share semantic associations with them. (c) GEOMETRY x CONSISTENT: widgets are more integrated into the geometry of the environment. All widgets rest on the closest surface while maintaining the relative locations within the layout same as the default layout. (d)GEOMETRY x SEMANTIC: widgets are more integrated into the geometry of the environment while being moved close to objects with shared semantic associations.

Each combination of the factorial design resulted in one unique layout in each environment. Participants rated their preference for each candidate layout on a discrete scale from 0 (least preferred) to 10 (most preferred). After rating all layouts, they completed a questionnaire: *(1) What factors did you consider while creating the default layout in Task 1? (2) What factors did you consider while adjusting the default layout for different rooms in Task 1? (3) What factors did you consider while rating your preferences in Task 2?*

4.2.1 Task 2 Procedure

In Task 2, participants first see the pre-built default interface layout (layout in Figure 3 (a)) and observe it. Then, they move to the four environments in the same sequence as in Task 1 where they could load each candidate layout (where each widget remains in the same LoD as in the default layout) using the number keys on the keyboard and adjust a slider to rate their preference using left and right arrow keys (Figure 5). The candidate layouts were presented as view-only and in random order. Participants could toggle between different candidate layouts to compare before finalising their rating. Participants could only proceed until they had rated all candidate layouts in each environment. An additional layout with widgets in scrambled locations was added (in random order) for screening participants who did not pay attention to the task (their data was excluded if the scrambled layout was rated higher than the others). In the end, participants completed the questionnaire.

4.3 Participants and Apparatus

We conducted the online study on the crowdsourcing platform Prolific.co. We recruited 30 participants (8 women / 22 men) with a mean age of 34 years ($Min = 19$, $Max = 59$, $SD = 11.27$) who successfully finished the study. Six other participants' submissions were rejected for failing attention checks. We requested the participants to be native English speakers from the U.S.. The average time to finish the study was 60.5 min ($Min = 23.1$, $Max = 102.35$, $SD = 25.35$). Participants rated their prior experience with MR (including VR and AR) on a scale of 0 (never used) to 10 (use every day) with a mean rating of 2.94 ($Min = 0$, $Max = 9$, $SD = 2.9$). Participants were paid the standard rate on Prolific (GBP10.55/hr).

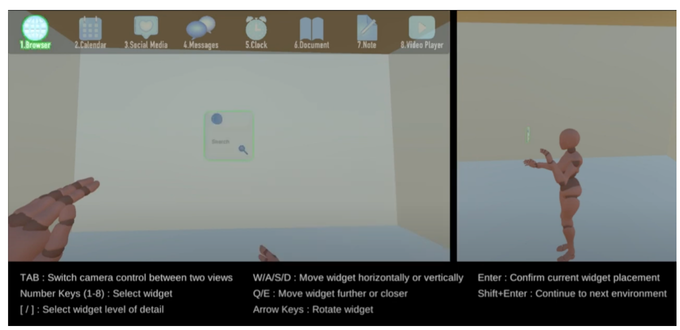

Fig. 4: UI for Task 1. Participants could place widgets from the menu bar into the environment using keyboard and mouse.

We deployed a Unity WebGL application online and provided a link on Prolific. We enabled participants to look around (rotating the virtual camera) using the mouse and place widgets using the keyboard (moving widgets with WASD keys). In both tasks, we presented a 1PP and a 3PP window to give participants a sense of the location of their bodies in the virtual environments to compensate for the lack of embodiment they would have in real AR interaction. Specifically, we made the hands visible to provide visual references to account for the visual distortion at the periphery of the FoV when user rotate the camera in the desktop VR environment, to provide a more accurate estimation of the location of the widget relative to the viewpoint when creating the default layout. The 1PP window had a horizontal FoV of 110°, simulating popular headsets (Figure 4-5). To ensure that participants get the same amount of visual information regardless of their display size, we built windowed Unity WebGL applications for both Study 1 and Study 3 with a fixed resolution and aspect ratio.

4.4 Quantitative Analysis and Results

In Task 1, we recorded each widget location relative to the 1PP camera in each environment, resulting in 1,200 data points; we also recorded

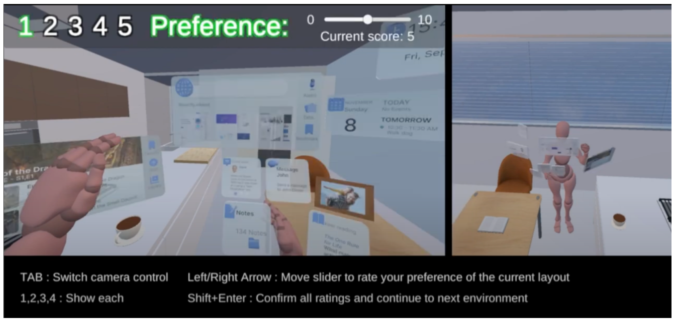

Fig. 5: UI for Task 2. Participants could load layouts using number keys, and rate their preferences using arrow keys.

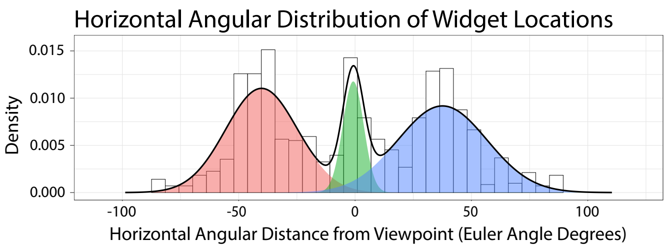

Fig. 6: Horizontal angular distribution of widget locations in all layouts that participants created/adapted in Task 1. The colours indicate the three components of the distribution.

240 usefulness ratings for all widgets. To understand the likelihood of widget placement at different locations in the egocentric space of users, we modelled the horizontal and vertical angular distributions, as well as distance distributions of widget placement.

4.4.1 Task 1: Widget Location Distribution

Figure 6 (a) illustrates the distribution of the horizontal angular distances between the widgets and the default gaze direction of participants when they entered a new environment. We fit a Gaussian mixture model to the observed distribution using the R package *mixR* [57]. The model has three components: Comp 1 ($\pi = 0.43, \mu = -40.21, sd = 15.41$), Comp 2 ($\pi = 0.13, \mu = -0.78, sd = 4.51$), and Comp 3 ($\pi = 0.44, \mu = 37.56, sd = 19.16$). Figure 7 (b) illustrates the vertical angular distribution of the widgets. We present the probability distribution ($\xi = -13.91, \omega = 27.60, \alpha = 1.08$) of a skew-elliptically contoured (SEC) distribution model fitted to the observed distribution using the R package *sn* [1]. The histogram in Figure 8 (c) illustrates the distribution of the distances between the widgets and the camera. We present the probability distribution ($\xi = 0.41, \omega = 0.27, \alpha = 2.73$) of an SEC distribution model fitted.

4.4.2 Task 1: Widget Placement and Usefulness

To analyse the effect of usefulness rating on widget angular distance, we removed outliers where the widgets were placed behind the avatar

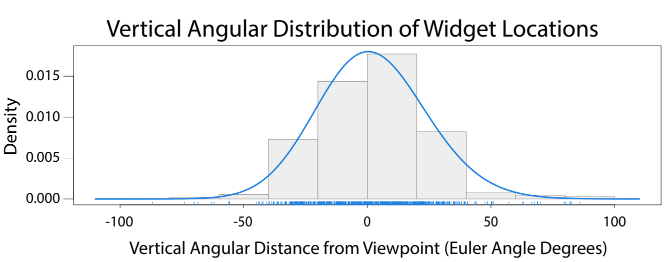

Fig. 7: Vertical angular distribution of widget locations in all layouts that participants created/adapted in Task 1.

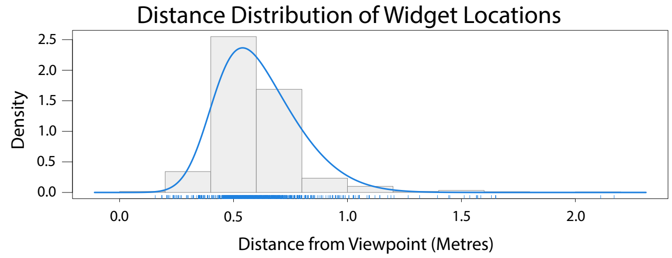

Fig. 8: Distance distribution of widget locations in all layouts that participants created/adapted in Task 1.

Task	Participants	Factor
Creation	15	Usefulness
Creation	12	Environment Visibility
Creation	10	Accessibility
Adaptation	23	Environment Visibility
Adaptation	21	Task
Adaptation	20	Consistency
Adaptation	11	Environment Geometry
Preference	10	Accessibility
Preference	10	Compactness

Table 1: Common strategies and factors that affected participants' layout creation, adaptation, and preferences.

(63 out of 1,200 observations). After inspection, we concluded that the outliers were irrelevant to usefulness because the participants' intention in those cases was to keep all widgets out of their view. We first used a simple linear regression to test if the USEFULNESS rating of widgets significantly predicted their angular distance (ANGLE) from the forward direction of the Unity camera at the start of the task (the avatar's looking direction) in the default layouts. The fitted regression model was: ANGLE = -1.48 * USEFULNESS + 46.20. The overall regression was statistically significant ($R^2 = 0.09,\ F_{1,230} = 23.17,\ p \leq .000$). It was found that USEFULNESS significantly predicted ANGLE ($\beta = -1.48,\ p \leq .000$). We then ran a linear mixed model analysis to test if USEFULNESS significantly predicted ANGLE in all layouts (including the default and the adapted layouts), with PARTICIPANT as a random effect. The fitted regression model was: ANGLE = -1.29 * USEFULNESS + 46.43. The overall regression was statistically significant ($R^2 = 0.24,\ F_{1,1134.8} = 66.51,\ p \leq .000$). It was found that USEFULNESS significantly predicted ANGLE ($\beta = -1.29,\ p \leq .000$).

4.4.3 Task 2: Layout Preference Rating

For Task 2, we recorded four preference ratings for each layout in each environment, which resulted in 480 data points. The ratings were on a discrete scale from 0 (least preferred) to 10 (most preferred). We estimated an ordered logistic regression to investigate whether STRUCTURE and STRATEGIES predict the preference rating of participants on the candidate adaptation layouts (on a scale from zero to ten). We found that the odds of COMPACT layouts being preferred was 5.920 (95% CI, 5.574 to 6.267) times that of layouts that matched the GEOMETRY of the environment, a statistically significant effect ($Wald\chi^2(1) = 110.024,\ p < 0.01$).

4.5 Qualitative Results

The post-study questionnaire yielded 90 responses. Two researchers carried out a general inductive analysis, using independent parallel coding to categorise notable factors mentioned by participants that corresponded with their layout creation and adaptation style [52]. We summarise the most frequently occurring factors in Table 1.

4.5.1 Layout creation

Fifteen participants commented that they considered the usefulness of the widgets when creating the layouts, and tried to bring the more useful widgets closer to them and/or make them more prominent in the layout. Twelve participants prioritised environment visibility in the layout. They typically achieved this by leaving the centre of the vision open for activities in the physical environment while arranging most widgets in the area covered by their peripheral vision. Ten participants prioritised layout accessibility to keep it close and always in view.

4.5.2 Layout adaptation

Most (23) participants commented that they considered the environment visibility when adapting the default layout to avoid conflicts between widgets and the environment, such as visual occlusion and intersection with objects. Though we did not specify an explicit task, 21 participants mentioned that they considered the types of tasks they would perform in the given environment (e.g., work in an office, relax in the bedroom) and adjusted the layout accordingly. Twenty participants noted the importance of consistency between adapted and default layouts. Such participants typically did not adjust the layout much in the new environments as long as there was no notable conflict between the environment and the widgets. Eleven participants adjusted the layout to suit the environment geometry by placing widgets on adjacent surfaces, such as the desk in the office.

4.5.3 Preference rating

The most common factors considered in the preference ratings were accessibility (10) and compactness (10). These participants indicated they preferred the widgets close to them for easier reach. They also preferred the widgets arranged in a compact style over being dispersed and integrated with the environment.

5 Study 2: VR Validation of Crowdsourcing

We replicated Study 1 in a face-to-face VR setting, using the same virtual environments and tasks. We aimed to see the effect of the embodied interaction experience on the data we measured and to validate the crowdsourcing approach as a potential cost-effective data collection method. We identified different trends in the results from 12 participants (Group 1) comparing with Study 1 regarding Task 2, which we interpret as due to inconsistent distance perception across desktop and VR environments. To isolate the effect of layout Structure while minimising the interference with perceived distance, we conducted the VR study with a second group of 12 participants (Group 2). For them, we only changed the setting in Task 2 by moving the Compact layouts further away from the participants at approximately the same distance as the Geometry layouts.

5.1 Participants and Apparatus

We recruited 24 participants (14 women / 10 men) with a mean age of 27.5 years ($Min = 19$, $Max = 38$, $SD = 4.8$) using the university mailing list. Twenty-three participants were right-handed. Participants rated their prior experience with VR and AR on a scale of 0 (never used) to 10 (use every day) with a mean rating of 4.63 ($Min = 0$, $Max = 10$, $SD = 2.83$). Each participant finished the study within an hour and was compensated with a AUD20 voucher.

We replicated the experimental Unity environment in Task 1 in a VR environment. We employed a Meta Quest Pro while remoting the Unity application on a desktop PC with a GeForce RTX 3090 graphics card through a Quest Link cable. Because the Meta Quest Pro has a horizontal FoV of 106°, we matched the FoV in the VR environment (110°) by moving the Unity camera back for 10 cm to ensure that participants see the same number of widgets as the participants in the online study in their starting viewport looking forward. We used the manual interactions supported in MRTK 3, including close interaction by manually manipulating objects and remote interaction by selecting and moving objects through a hand ray and a pinch gesture. To replace the menu bar in Study 1 (Figure 4-5), we employed a hand menu (Figure 9), which is a popular interaction style with MRTK.

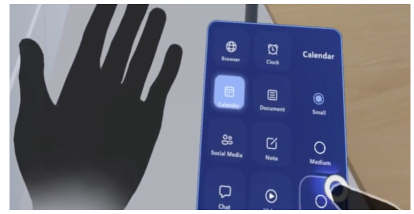

Fig. 9: Hand menu for selecting widgets and adjusting their LoD for placement in the virtual environment in VR.

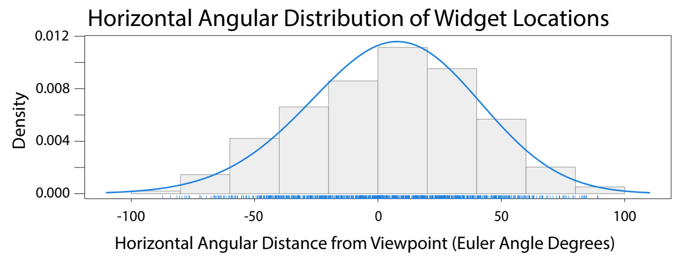

Fig. 10: Horizontal angular distribution of widget locations in all layouts that participants created/adapted in Task 1.

5.2 Procedure

After introducing the study, we guided participants through a custom-designed hand interaction tutorial requiring them to perform object manipulation tasks using near-hand and remote hand-ray interaction. Participants needed to finish interaction tasks in the tutorial to proceed to the formal tasks in the study. After rating the usefulness of the widgets, participants loaded widgets from their hand menu to create the default interface layout and then adjusted the layouts in the four environments. Participants loaded and rated candidate layouts using the hand menu instead of the keyboard in Study 1.

5.3 Quantitative Analysis and Results

We recorded 960 widget locations and 192 usefulness ratings in Task 1, and 384 ratings in Task 2. Similarly to Study 1, we modelled the horizontal and vertical angular distributions, as well as distance distributions of widget placement.

5.3.1 Task 1: Widget location distribution

Figure 10 (a) illustrates the horizontal angular distribution. We present an SEC distribution model fitted to the observed distribution ($\xi = 29.41$, $\omega = 42.32$, $\alpha = -1.03$). Figure 11 (b) illustrates the vertical angular distribution of the widgets. We present the probability distribution of an SEC distribution model fitted to the observed distribution ($\xi = 23.40$, $\omega = 30.91$, $\alpha = -1.81$). Figure 12 (c) illustrates the distribution of the distances between the widgets and the participants, with the probability distribution ($\xi = 0.65$, $\omega = 0.77$, $\alpha = 6.58$) of an SEC model fitted.

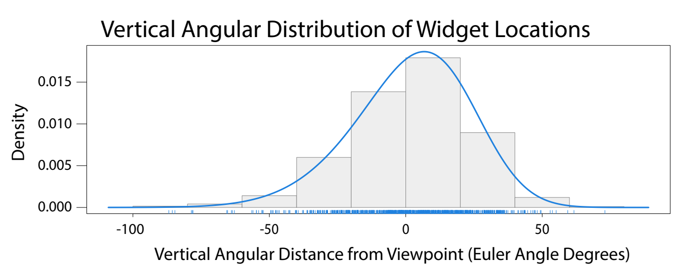

Fig. 11: Vertical angular distribution of widget locations in all layouts that participants created/adapted in Task 1.

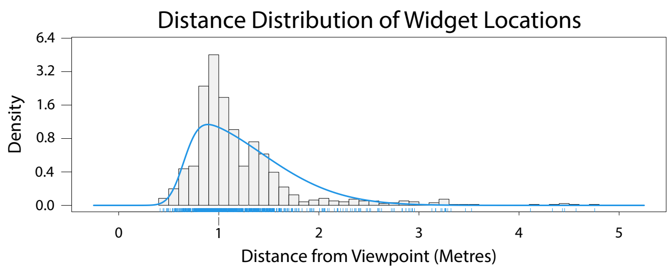

Fig. 12: Distance distribution of widget locations in all layouts that participants created/adapted in Task 1

Task	Participants	Factor
Creation	20	Usefulness
Creation	13	Environment Visibility
Adaptation	23	Task
Adaptation	17	Consistent
Adaptation	13	Environment Geometry
Adaptation	11	Environment Visibility

Table 2: Common factors that affected participants' layout creation and adaptation behaviour in VR (Task 1, Study 2).

5.3.2 Task 1: Widget placement and usefulness

We first used a simple linear regression to test if the USEFULNESS rating of widgets significantly predicted the ANGLE they are from the forward direction of the Unity camera at the start of the task in the default layouts. The fitted regression model was: ANGLE = -2.65 * USEFULNESS + 48.71. The overall regression was statistically significant ($R^2 = 0.20,\ F_{1,190} = 46.34,\ p \leq .000$). It was found that USEFULNESS significantly predicted ANGLE ($\beta = -2.65,\ p \leq .000$). We then ran a linear mixed model analysis to test if the USEFULNESS significantly predicted ANGLE in all layouts (including the default and the adapted layouts), with PARTICIPANT as a random effect. The fitted regression model was: ANGLE = -1.32 * USEFULNESS + 44.61. The overall regression was statistically significant ($R^2 = 0.28,\ F_{1,957.21} = 41.48,\ p \leq .000$). We found that USEFULNESS significantly predicted ANGLE ($\beta = -1.32,\ p \leq .000$).

5.3.3 Task 2: Layout preference rating

We estimated ordered logistic regressions to investigate whether STRUCTURE and STRATEGIES predict preference rating on candidate adaptation layouts (on a scale from zero to ten). For Group 1, we found that the odds of GEOMETRY layouts being preferred was 11.020 (95% CI, 10.718 to 11.322) times that of COMPACT layouts, and the odds of SEMANTIC layouts being preferred was 1.842 (95% CI, 1.584 to 2.1) times that of CONSISTENT layouts, a statistically significant effect, $Wald\chi^2(2) = 74.398,\ p < 0.01$. For Group 2, we found that the odds of COMPACT layouts being preferred was 3.446 (95% CI, 3.18 to 3.712) times that of GEOMETRY layouts, a statistically significant effect, $Wald\chi^2(1) = 22.487,\ p < 0.01$. CONSISTENT and SEMANTIC yielded no significant difference.

5.4 Qualitative Results

The questionnaire generated 72 responses. After analysing the data following the same approach as in Study 1, we summarise the most frequently occurring factors in Table 2-3. For layout creation and adaptation, twenty participants commented that they placed the high-usefulness widgets closer to them and/or made them more prominent in the layout. Thirteen participants prioritised environment visibility. Most participants commented that they adjusted the layout according to the tasks they envisioned in the environment. Seventeen participants mentioned/demonstrated the importance of consistency between adapted and default layouts. Thirteen participants considered environment visibility when adapting the default layout to different environments. Eleven participants adjusted the layout to suit the environment geometry by placing widgets on adjacent surfaces. We analysed feedback on preference ratings for the two groups separately. **Group 1:** Six participants mentioned that they considered the task that they may perform in the given environment. Participants also mentioned the importance of the visibility of the environment (5) and of the layout as a whole (5). They also mentioned the importance of keeping a comfortable distance from the layouts. **Group 2:** Nine participants mentioned the importance of environment visibility and commented that they preferred the candidate layouts that occluded the environment as little as possible. Eight participants specified a preference for compact layouts with better-defined structures to separate them from the environment. Six preferred visibility of the entire layout for finding widgets easily.

Group	Participants	Factor
1	6	Task
1	5	Environment Visibility
1	5	Distance
1	5	Layout Visibility
1	4	Distraction
2	9	Environment Visibility
2	8	Compactness
2	6	Layout Visibility

Table 3: Common factors that affected participants' preference for different layouts in VR (Task 2, Study 2).

6 DISCUSSION OF STUDY 1 AND STUDY 2

6.1 Comparison between Results from the Two Studies

We found that the first 12 participants in the VR study produced inconsistent results in Task 2. More specifically, GEOMETRY layouts were significantly preferred over COMPACT layouts. After closely inspecting the data, we postulated that it was due to the inconsistency between the perceived distances in different technical environments. In Study 1, we set the horizontal FoV of the 1PP view as 110°while simulating a similar effective FoV that would be offered by a future AR device (matching the FoV on current popular VR devices [8]). To ensure text-readability on the desktop environment while accounting for different screen sizes that participants would complete the study with, we placed the COMPACT layout at a 45 cm distance from the camera (optimal reading distance in AR with matching font size, as per [38]), same as the default spawning distance of the widgets. Whereas we matched the FoV in VR by adjusting the camera position, the distances from the COMPACT layouts were still perceived as closer than that on the desktop environment due to the perspective distortion in the desktop simulation (Figure 3), and to the known fact that egocentric distance is underestimated in VR [25, 45]. Consequently, participant disliked COMPACT layouts in VR due to the close distance and the occlusion.

The results from Task 2 offer insight into the reliability of different types of data obtained from Study 1. These results indicate that desktop simulation is not suitable for eliciting layout creation due to widget placement distribution data that deviates from results obtained using VR interaction. Further, after addressing the distance perception issue with a simple adjustment of the layouts, we found similar trend of user preference across the two platforms, indicating the suitability of this crowdsourcing approach for eliciting preference data.

6.2 Layout Distributions

The statistical models fitted to the widgets' angular and distance distributions can serve as prior probability distributions for widget placement in future studies on AR interface adaptation. We found interesting differences in the patterns of the distributions between the online study and the VR study, which we attribute to the differences in display and input modalities. In Study 1, because users controlled widget movements using a keyboard, the widgets always travelled one degree of freedom at a time, e.g., left when pressing "A" and up when pressing "W". As a result, the widgets in the final layouts were better aligned with each other, as illustrated in the three narrower distributions in the horizontal angular distribution (Figure 6). In Study 2, the horizontal angular distribution was a negatively skewed normal distribution. We interpret this as a consequence of most participants in the VR study being right-handed. As such, they were more likely to place more widgets on their right. Also, because of the additional freedom in object manipulation, the widgets were more evenly distributed around the participant's body (Figure 10) instead of forming the tri-modal distribution observed in the online study (Figure 6).

6.3 Factors Independent of the Environment

Usefulness of widgets: Many of the factors considered while creating and adapting AR interface layouts were independent of the environment. For instance, across all environments, participants were more likely to arrange widgets perceived as more useful directly in front of them. This finding was consistent in both studies and in both the creation of the default layouts and their subsequent adaptations. The coefficients in the fitted linear regressions ranged from -1.29 to -2.65, providing strong evidence that future adaptive AR interfaces should keep the more useful widgets near the centre of the layout. In Study 3, we combine this finding with the probability distributions of widget locations to match more useful widgets with more useful locations in the space.

Environment visibility: Being able to see the physical world was considered an important factor by most participants (Table 1-3). This can also be observed in the layouts they created (e.g., in Figure 1) and in the horizontal distribution of widgets in the online study (Figure 6). Although the convergence of widgets near 40 degrees to their left and right in the distribution was likely due to the effect of the input device, it nevertheless demonstrates participants' intention of keeping widgets out of the centre of their FoV and maintaining good visibility of the physical environment, for either seeing task-related objects or for potential mobility in the environment. These findings echo previous work that found user preference for adaptive AR layouts that do not interfere with secondary tasks in the physical world [26].

Layout consistency and compactness: We found that participants valued the consistency of the layouts while adapting them to different environments. Consistency was valued both in keeping the relative positions of widgets within the layout and in maintaining the structure of the layout, as demonstrated by participants' preference for COMPACTNESS in Task 2. Previous works found that users can benefit from spatial memory supported by landmarks in 2D UIs [46]. However, this benefit may be hindered by the variation of widget locations along the depth dimension in AR [7], which is likely to occur when AR content directly augments objects in the physical environment. Consequently, most participants in Task 2 preferred layouts with more clearly defined structures with widgets arranged to have similar distances towards the viewpoint over the layouts, with widgets augmenting surfaces and objects scattered in the environment. The compact structures of the layouts could also have contributed to reducing visual clutter, which previous work has found to negatively affect the user experience in AR [51]. Another potential benefit of compact structures is less occlusion of the environment, consequently providing good visibility. Other environment-specific factors seemed overshadowed by the aforementioned factors, such as the semantic relationship between the widgets and the objects in the environments.

7 OPTIMISATION-BASED LAYOUT ADAPTATION SYSTEM

Study 1 and Study 2 gave us: (1) Factors that impact user preferences for adaptive placement of AR interface layout; (2) Probabilistic models of widget location distributions in AR interface layout creation and adaptation; (3) Suitability of online crowdsourcing for preference elicitation using pre-built layouts. Recognising these limitations and opportunities, we designed an optimisation algorithm and integrated it into the same virtual environment employed in Study 1 and Study 2. We built the optimisation system based on findings from the first two studies, including the quantitatively and qualitatively learnt factors considered by participants while adapting their personal AR interfaces, and the probabilistic models of widget location distributions. We aimed to use the system to create adaptation outputs that cover a diverse range of layouts that prioritise different factors, and deploy them for online crowdsourcing to elicit user preference data from a large sample. The goal is to derive a probabilistic model that can predict user preferences for AR interface layout adaptation represented as a set of optimum weighting coefficients for different factors.

7.1 Egocentric Candidate Widget Container Generation

To define a finite set of possible locations as unit volumes of the environment for the optimisation algorithm to match with widgets, we divided the space surrounding the user (represented by the 1PP Unity camera) into individual CANDIDATE CONTAINERS facing the user (Figure 13). The container generation process is controlled by a set of parameters defining the size of the containers, including the horizontal angular coverage which determines the number of columns, the number of rows covering the vertical space, the number of layers, the distance between layers, and the distance from the first layer to the user's viewpoint. Based on the distance distribution of widgets in participant-created layouts from Study 2 (Figure 12), we defined the distance from the nearest layer to the Unity camera as 0.7m and generated five layers with gaps of 0.2m in between. We generated containers to fill the 180°horizontal space in front of the camera in six rows. The containers cover the volume of egocentric space surrounding the user that is most likely to be used to place widgets. The containers are disabled during the generation process if the system detects collisions between them and objects in the environment. We generate containers of three different sizes to fit the three different LoDs of the widgets (small, medium, and large), and set constraints in the optimisation program to prevent intersecting containers from being simultaneously occupied.

7.2 Optimisation Factor Definition

We define the optimisation task as matching AR widgets with the optimum container (Equation 1), to maximally reward the sum of the values of a set of factors that may positively impact user preferences for adapted AR interface layouts. We define these factors as follows while x represents a match between a widget and a container.

$$x_{w,c} = \begin{cases} 1 & \text{if widget } w \text{ is placed in container } c \\ 0 & \text{otherwise} \end{cases} \tag{1}$$

7.2.1 Usefulness (U)

In Studies 1 and 2, we found that participants tended to arrange more useful widgets directly in front of them near the centre of their viewport. To capture this need, we defined the factor Usefulness (U) to reward the placement of more useful widgets in containers that are more likely occupied by widgets (Equation 2). It consists of two components: u_w stands for the usefulness of the widget, and u_c stands for the usefulness of the container. We define u_w based on the mean widget usefulness rating in Study 1 and Study 2, representing the likely values as perceived by AR users. We define u_c as the probability of the location of the container to be used for placing widgets. We used the probability models of horizontal, vertical, and distance distributions of widgets from user-created layouts in Study 2 (Figure 10-12) to calculate u_c.

$$U = \sum_{w} \sum_{c} x_{w,c} \max\ u_w * u_c \tag{2}$$

7.2.2 Environment Visibility (EV)

From user behaviour and feedback in Studies 1 and 2, we found that users liked to create and adapt their AR interfaces such that the widgets

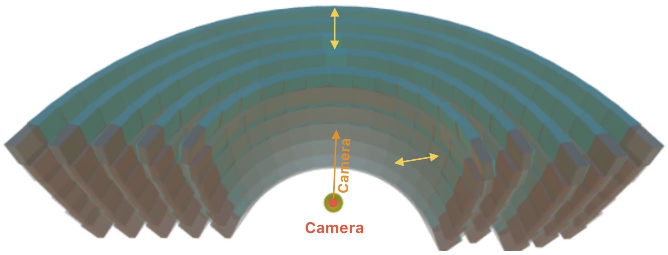

Fig. 13: Containers generated for optimisation. The location (red) and direction (orange) of the camera is used for calculating Compactness. The yellow arrows indicate examples distances used for calculating Planar and Distance Consistency.

do not obstruct their views of objects in the environment. To capture this need, we implemented this factor to reward layout in which salient objects in the environment are not occluded by widgets from the user's viewpoint (Equation 3). We marked all containers around the users that occluded objects, and penalised widget placement in them.

$$EV = \sum_{w}\sum_{c} x_{w,c} \min\ EV_{w,c};$$
$$EV_{w,c} = \begin{cases} 1 & \text{if container } c \text{ obstructs salient objects} \\ 0 & \text{otherwise} \end{cases} \tag{3}$$

7.2.3 Planar Consistency (PC) and Distance Consistency (DC)

From Studies 1 and 2, we learned that users value the consistency between the adapted interface layout and the default layout previously created by themselves. To enable the optimisation algorithm to preserve these consistency considerations, we further disentangle this need into two factors. Planar Consistency rewards widget placements where the widgets deviate the least from their locations in the default layout along the X and the Y axis with the user's viewpoint location as the spatial reference (Equation 4). Distance Consistency rewards widget placements where the widgets deviate the least from the default layout along the Z axis from the user (Equation 5).

$$PC = \sum_{w}\sum_{c} x_{w,c} \min XYDistance_{w,c} \tag{4}$$

$$DC = \sum_{w}\sum_{c} x_{w,c} \min ZDistance_{w,c} \tag{5}$$

7.2.4 Compactness (C)

Participants in Studies 1 and 2 expressed that they would prefer the layouts to be adapted into well-defined structures instead of spanning. The widget distribution also shows that the central area in the user's view is preferred for placing widgets. We implemented this factor to reward smaller angular distances between the vector from the viewpoint to the container and the forward vector of the camera (Equation 6).

$$C = \sum_{w}\sum_{c} x_{w,c} \min\ Angle(c, camera, \overrightarrow{camera}) \tag{6}$$

7.2.5 Surface Attachment (SuA)

To account for users' needs to adapt the layouts according to the surface geometry of the environments while benefiting from AR's environment augmenting capabilities, we implemented the Surface Attachment factor to reward widget placement on salient surfaces close to the user. We define the containers immediately above the surfaces as attachment containers where widget placement is rewarded (Equation 7).

$$SuA = \sum_{w}\sum_{c} x_{w,c} \max\ SuA_{w,c};$$
$$SuA_{w,c} = \begin{cases} 1 & \text{if container } c \text{ is above a surface} \\ 0 & \text{otherwise} \end{cases} \tag{7}$$

7.2.6 Semantic Association (SeA)

Previous works found that users would like to place AR widgets close to physical objects in the environment that share semantic associations with them [6], even though we did not find a significant correlation in the previous two studies. Nevertheless, to validate this effect, we implemented a Semantic Association factor to reward widget placements satisfying this need. To calculate the semantic associations between widgets (w) and objects (o) in the environment, we ran each object through Google VisionAI to obtain their names that would likely be recognised by universal computer vision algorithms. Then, we calculated the word similarities between the names of the widgets and the names of the objects using GloVe [41]. The Semantic association factor rewards widget placements in containers closer to objects that share larger semantic similarities with the widgets (Equation 8).

$$SeA = \sum_{w}\sum_{c} x_{w,c} \max_{o} \frac{similarity_{w,o}}{distance^2_{c,o}} \tag{8}$$

7.3 Optimisation Constraints

We defined a set of constraints as a part of the optimisation algorithm to prevent undesired outcomes: (1) Each widget can be placed only once; (2) Each container can be occupied by only one widget; (3) Intersecting containers cannot be simultaneously occupied; (4) Widgets cannot occlude each other by more than half the visible surface area.

7.4 Objective Function

With the seven factors, we define the objective function in Equation 9, where $\beta 1 - \beta 7$ are coefficients that determine the weighting of each factor. We implemented the optimisation algorithm in the virtual environments used in Study 1 and 2 with the Gurobi v10 solver [21]. The system can simulate user input of AR interface placement adaptation by manipulating the weighting coefficients to prioritise different factors. Figure 14 shows examples of outputs of the optimisation.

$$\arg\max_{w,c}\ \beta_1 * U + \beta_2 * EV + \beta_3 * SuA + \beta_4 * C + \beta_5 * PC + \beta_6 * DC + \beta_7 * SeA \tag{9}$$

Because each factor has a unique purpose and range of possible values, we need to prevent the optimisation results from being biased towards overpowering factors that produce large values. To this end, we calculated the values of all seven factors for the user-created interface layouts in Study 2 as if they were created using the optimisation system. Then we obtained the most likely (95%) value ranges of those factors using the `hdr.den` function in the `hdrcde` R package, which provides density plots with highest density regions [23,47,54]. Using these value ranges, we normalised the output value of each factor for optimisation. The normalisation helps produce layouts that are more likely preferred by users and brings all factor values within the range of 0-1 for easier control of the weighting coefficients.

8 Study 3

After abstracting the set of factors in the optimisation system based on prior knowledge learned from Studies 1 and 2, we conducted a final online crowdsourcing study. We aimed to collect user preference data from a large sample to help us build a probabilistic model that is able to predict universal user preferences for AR interface layout adaptation by quantifying the effects of different factors. This model will provide us with a first empirical understanding of user strategies and preferences in AR interface layout adaptation and can be used for future AR interface adaptation algorithms as a prior model.

8.1 Study Design

From Studies 1 and 2, we learned that online crowdsourcing is suitable for eliciting layout preference data. To efficiently and reliably elicit such data, we opted for a pairwise comparison approach instead of preference rating on a numeric scale to save time. We used the optimisation system to simulate user-created layouts based on previous data of user-created layouts from Studies 1 and 2 in the same virtual environments. We made minor adjustments to the environments to

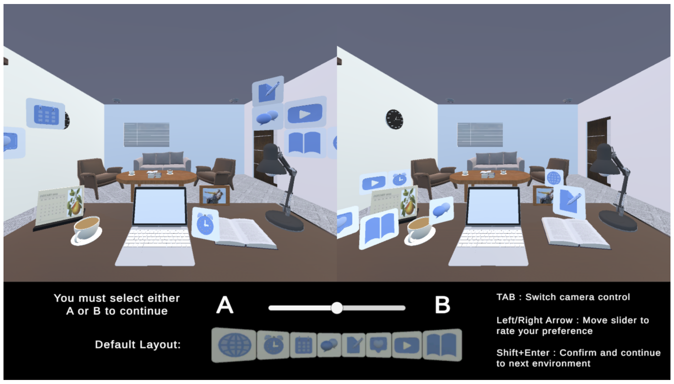

Fig. 14: Example UI for Study 3. Participants used the mouse to look around and moved the slider with the keyboard.

introduce more potential variations in the optimisation results (e.g., moving the calendar away from the clock in the kitchen).

8.2 Using Prior Knowledge from Studies 1 and 2

We used the mean widget usefulness rating value from Studies 1 and 2 as the default values for u_w and used the probability distributions of widget locations modelled with data from Study 2 to calculate u_c in the Usefulness factor. We used a "non-informative" default layout for Study 3 by arranging all widgets in the row of containers directly in front of the user's viewpoint, similar to the "universal menu" on Meta Quest devices. Participants were informed that the adapted layouts that were subsequently presented to them for comparison were adapted from this default layout. We aimed to create adapted layouts while controlling for the different amplitudes of effects of each factor. Because each factor has unique possible range of value (e.g., whereas SuA is binary, U is the product of two continuous values), it is challenging to determine appropriate values for the weighting coefficients to ensure that no factor would overpower the others in the created layouts. Therefore, we normalise the factors using prior knowledge from Study 2.

8.3 Participants and Apparatus

We conducted the study on Prolific.co with 250 participants (99 female / 151 male) with a mean age of 39 years ($Min = 18$, $Max = 71$, $SD = 11.9$) who successfully finished the study. We requested the participants to be native English speakers from the U.S. with access to desktop computers and a minimum of 85% approval rate. The average time to finish the study was 19.4 min ($Min = 5.57$, $Max = 60.45$, $SD = 9.25$). Participants were paid the standard rate on Prolific (GBP9.02/hr). Each participant made eight comparisons per environment, totalling at 32.

Using the normalised factors, we generated layouts by setting each coefficient as 0 or 1. By enabling/disabling each factor in the optimisation, we separate their effects in the generated layouts and introduce the most variance in factor priority while requiring the minimum number of population samples. This gave us $2^7 - 1 = 127$ unique layouts (the optimisation has no solution when all factor values are zero), arranged in 8001 unique pairs for comparison. We distributed the 8001 pairs of layouts randomly into the four virtual environments. We developed a new Unity WebGL interface that shows each pair of layouts side-by-side. Participants can switch between camera controls for the two windows to view and select their preferred layout by moving a slider while also seeing the default layout for reference (Figure 14).

8.4 Procedure

We first provided textual and image instructions to introduce the purpose of the study and its scenario, followed by a set of scenes showing the details of the widgets, including all LoDs to show how they are supposed to be used. Then, participants were presented with four candidate layout pairs in each environment, where they could select their preferred one using the arrow keys on the keyboard to adjust a slider (Figure 14). To control for the variance in the size of widgets, we used the small size with an icon to represent all widgets in the generated layouts. Participants could only proceed after making their choice for each pair. We used an obviously worse layout in an extra pair as attention check and removed the data from 19 participants who failed.

Table 4: Results from the conditional logistic (`clogit`) regression modelling of the preference data, represented by the median regression coefficients and their standard deviations (SD). We report the odds ratios (OR) to show the probabilistic effects on the linear scale.

Factor	Coefficient	SD	OR
Usefulness	0.079	0.035	1.082
Environment Visibility	0.060	0.009	1.062
Planar Consistency	0.092	0.025	1.096
Distance Consistency	0.194	0.030	1.214
Compactness	0.170	0.030	1.186
Surface Attachment	0.075	0.008	1.078
Semantic Association	0.012	0.010	1.012

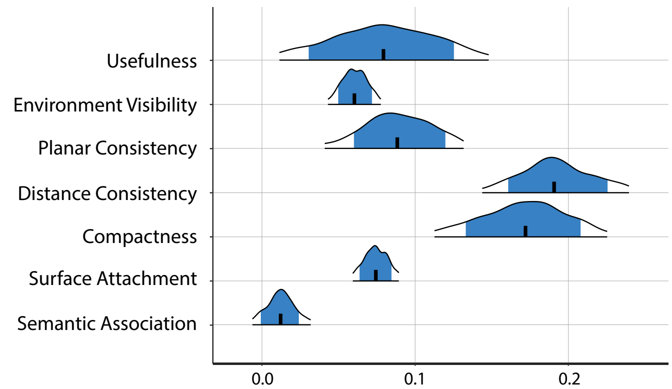

Fig. 15: Probability distributions of the regression coefficients of each factor from the conditional logistic regression model. The black lines and the blue areas indicate 95% and 80% credible intervals, respectively.

8.5 Analysis and Result

To provide an understandable probabilistic model that describes the effects of different factors on user preference for the interface layout, we adopted a Bayesian modelling approach. With data from 8001 pairwise comparisons, we built a Bayesian conditional logistic (`clogit`) regression model using the `stan_clogit` function in the `rstanarm` R package to quantify the effects of the factors [4, 18]. We calculated the values of the seven factors in the layouts generated by the optimisation system and used them as predictor variables. We used participants ($SD = 1.280$) and environments ($SD = 1.388$) as random effects while setting the strata as each pair of layouts. We fit the model using a weakly informative prior. We report the results in Table 4 and present the probability distributions of regression coefficients in Figure 15.

9 Discussion of Results from Study 3

The probabilistic model largely validates our quantitative and qualitative findings from Study 1 and Study 2. We found positive effects on user preference for adapted layouts across all factors. In this section, we distil ***Guidelines*** for future adaptive AR interfaces by discussing the results, and reflect on how they address the research questions.

9.1 Effects of Layout Structure

Distance Consistency and Compactness had the largest effects on user preference. We believe this is because they reflect user preferences for the spatial structures of the layouts, which is an important spatial feature of the adaptation, given limited contextual information. The effect of Distance Consistency was reflected earlier in the findings from Studies 1 and 2, where we found that participants preferred to have widgets not too far from them for easier access. The narrower distance distribution of widget locations (Figure 12) than the angular distributions (Figure 10,11) also suggested that user preferences for widget distances were more universal than for their angular dispositions. From these results, we distil ***Guideline 1: Adaptive AR interfaces should prioritise keeping the virtual elements at similar and consistent distances from the user.*** The less effect from Planar Consistency suggests that users prioritise it not as much as keeping the widgets within closer layers of distance relative to their viewpoint. This may be explained by the larger effect on Compactness, which suggests that participants preferred layouts in which widgets were more closely arranged from each other. The visibility of widgets within the FoV in compact layouts saves participants from seeking the widgets in changing environments, which they might need to do with layouts that are more spread out, where Planar Consistency may be more important. From these results, we distil ***Guideline 2: Adaptive AR interfaces should maintain a clear visual structure of the layout of the virtual elements by arranging them close to each other.***

9.2 Effects of Environment and Widgets

Environment Visibility and Surface Attachment both had positive effects of modest sizes, indicating that although participants would like to adjust the layouts according to the geometry and salient features of the environment, these needs are not as important as the factors concerning the structure of the layouts. Notably, the variances in the effects of these two factors are observably smaller than that of most other factors. This possibly suggests that the preference for adapting AR interface to fit the physical environment is more universal than for those concerning the structures of the layouts.

The effect of Usefulness confirms our finding in Studies 1 and 2 that more useful widgets are more likely to be placed at the more useful locations around the user's body. We observe a large variance in the effect of Usefulness, which could be due to the individual differences in evaluating how useful different widgets are, on top of the individual preferences for ideal locations to place those widgets around the body. The marginal effect of Semantic Association indicates that whereas some participants may consider this factor, it is not as important as the other factors for producing adapted layouts that would likely be preferred by users. Whereas the semantic associations between virtual interface elements and physical objects in the environment have been explored as a novel factor in AR interface adaptation [6, 30, 44], there lacked empirical evidence supporting its importance in those works. Our results suggest that it may not be as prioritised by users as other factors about the layout structure and the geometry of the physical environment. We argue that semantic associations between AR interfaces and physical environments may have different significance depending on the context. For instance, a user may want a virtual calendar widget to be close to a physical calendar if they complement each other in the given task, but they may also prefer them to be placed far from each other if they want to be able to check their schedule no matter which direction they are looking. These potential different interpretations and needs of semantic associations between AR widgets and physical objects not only depend on the task information but may also depend on users' personal interpretations and spontaneous intentions, which make it questionable to be abstracted as an individual factor for optimisation-based adaptive placement of AR interface layout. Based on our findings, we suggest that semantic associations should not be a default factor to consider for environment-adaptive AR interface placement when no more task-related contextual information is available. From these results, we distil ***Guideline 3: Adaptive AR interfaces should take caution in defining and integrating factors related to user-perceived relationships between virtual elements and the physical environments as well as the objects in them.***

9.3 The Value of Environment-Adaptive AR Interface

While previous work that proposes novel algorithms and methods for adaptive AR interfaces is abundant, they often either focus on specific contexts like mobility [14] or lack sufficient support by empirical knowledge [6]. These works often proposed methods while assuming contextual knowledge beyond the capabilities of the AR headsets, such as the task that the user planned to perform. The specific contextual scopes, the lack of evidence in evaluation, and the unrealistic assumptions of contextual information make it challenging to generalise the system contributions or modelling results from these studies to benefit future work [40, 55]. To explore these more advanced features of adaptive AR interface, we first need a basic understanding of how users would like their personal AR workspace to adapt only to the change of physical environment by isolating its effect.

Recognising these challenges in addressing RQ1, we chose to focus on the fundamental understanding of how the change of physical environments affects user preference for AR workspace adaptation while minimising the influence of individual variance in assumptions related to other use contexts. To this end, we created a scenario with a realistic context in which future users may use AR as their personal computer. We instructed participants to create a default AR workspace layout "just like how they arrange their smartphone home screen" not to suppress interpretations of contexts but to allow us to understand user preference without the confound of evoking specific interpretations consistently across participants. The result of the study is a probabilistic model using data collected from a large population in a controlled setting where the only consistent change factor was the physical environment. This model addresses RQ2 by contributing the set of odds ratio that quantitatively reflect the effect of the different factors on user preference of adaptive AR interface layout. Despite individual differences in contextual factors that we could not control, this model still represents the fundamental understanding of how users would like AR workspace layouts to adapt to new environments. We believe this probabilistic understanding can benefit future work exploring more diverse use contexts and more advanced computational methods.

An application area that can directly benefit from the current probabilistic model is for one-shot adaptations of the home screen layout for AR interfaces. Current state-of-the-art AR devices, such as Meta Quest Pro, Apple Vision Pro, and Microsoft HoloLens, all adopt window-based home screen menu layouts. While we could expect future systems to incorporate 3D layouts, the concept of the "home screen" is likely to stay for longer until or even after AR becomes the next-gen personal computer to cater for habitual uses and expectations from users. Such home screen layouts, similar to those on smartphones, are task-agnostic. Especially when users start AR systems in new environments, the only contextual information that is likely available to the adaptive system is the geometric features of the environment. Such use cases may become increasingly common as the availability of AR devices increases. The probabilistic model contributed by this work can directly inform such use cases by providing baseline probability distribution as prior knowledge for users to build on and optimise. Additionally, if users choose to arrange their home screen layouts for specific tasks, they are unlikely to expect the widgets in these layouts to change often because of the choice of arranging them as "home screens". Even when task-related assumptions are made by users, as long as they do not change across different physical environments or as long as they are consistently unknown, the current results still inform AR workspace layout adaptations to new environments as reliable prior knowledge.

9.4 Future Use of the Model and Data

With the open-source model and data, future works can easily replicate the study results or experiment with alternative analysis approaches. One interesting direction of work is exploring the feasibility of using a Bayesian Optimisation routine to adaptively generate the most likely informative tasks for participants while negotiating the trade-off between computing power and the scale of concurrent deployment of the study [19]. Another direction is to use multi-objective optimisation approaches for interface adaptation, as demonstrated as feasible by recent work [24]. While the probability distributions of the factors identified in this work can inform *a priori* articulation of preferences, the study apparatus and procedure documented in the paper can also be used for implementing online interface adaptation following *a posteriori* approaches [36]. Future works along this direction can also investigate how the interface layouts can adapt to user behaviour online, such as hiding widgets with similar functions to those closed by the user.

10 Limitations and Future Work

We experimented with crowdsourcing as a cost-effective way to collect user data for informing adaptive AR interface design by replicating the same procedure online and face-to-face. Whereas we found that this approach is suitable for our study on layout preference elicitation, we do not claim that online crowdsourcing could replace studies in VR or AR. The keyboard and mouse input may hinder participants' layout creation and adjustment in Studies 1 and 2, as illustrated by the distribution in Figure 6, which may not accurately reflect how they would place widgets in realistic contexts while wearing AR or VR headsets. Future work should be aware of the potential effects from different screen sizes and the trade-off between the FoV and the perspective distortion in desktop and VR environments. Further, the visual presence of the hands of the avatar in Study 1 could have prevented participants from placing widgets at locations that may collide with or be occluded by the hands. Though the horizontal distribution data suggests that the directions toward the hands were preferred for widget placement (Figure 6), future work should take the hand visibility into consideration when interpreting those findings.

We asked participants to adapt and assess layouts for each environment only with a loose definition of the task (e.g., working in the office and relaxing in bed), to maximise ecological validity, and to contribute universal prior knowledge of user preferences in adaptive AR interface. We did this because, in practice, this information is unknown to the system. However, when users have specific tasks in mind, the task characteristics can also affect the relative importance of different layout properties. More work is required on how to best recognise relevant tasks and adapt the interface accordingly. We chose a set of widgets based on popularity in mobile platforms as the most reliable indicator for future popular AR apps. However, they may not accurately represent the applications that the participants in our sample regularly used. While we tried to control for these effects by operationalising them in our analysis as the perceived usefulness of widgets, future work could explore using more diverse types of environments and widgets to cover more use case scenarios of adaptive AR interface, potentially supported by our crowdsourcing approach. Further, the design choices of the widgets and the descriptions of the scenario may bias participants towards imagining adaptive interfaces for general-purpose home screen layouts, which limits the generalisability of the results to task-specific use contexts. Additionally, we presented the options to place the widgets differently in Study 1 (Figure 4) and in Study 2 (Figure 9), and limited the LoD option in Study 3, which could have affected the orders in which the widgets were loaded into the environments.

Though we chose common environments that users might encounter in their day-to-day life, we acknowledge that users' prior experience (potentially different among the three studies due to educational and cultural backgrounds) with the environment creates cues in their spatial memory that might affect where they place their widgets. Similarly, different experiences and levels of expertise with AR/VR interactions among participants could also induce unpredictable differences in their layout placement behaviour. This could also have had an effect on how participants imagined the widget to be interactive in reality. For instance, while they may prefer to keep widgets that afford fine manipulation close to their bodies for easier access by hand, the widgets that are mainly for information display could be placed further away. Future work should consider different interactivity of AR widgets, and could investigate how novel interaction techniques, such Gaze&Pinch that has become available on AR devices, may affect user preference for adaptive AR layouts [42].

We simulated an AR scenario using a virtual environment displayed through desktop and VR. We made this experimental design choice for better control over the simulated physical environments in terms of the consistency and variance of the existence and placement of salient objects within them. Moreover, it enabled us to fit the environments with a universal use case scenario that minimises individual differences in personal associations, which might be evoked more easily with photographic scenes and objects. Future work could investigate the potential difference between virtual and photorealistic scenes for eliciting user input and preference for AR interface adaptation. Similarly, future works could investigate the effect of rendering transparency of AR widgets in see-through and video pass-through contexts on user preference for factors such as Environment Visibility.

We generated the candidate layouts for Study 3 by setting the weighting coefficient of each factor to 0 or 1. While we made this choice to obtain a reasonable number of outputs to deploy in the study, sampling more values between this range could help produce more fine-tuned results. Finally, interactions or non-linear dynamics could not be specifically covered by our optimisation approach or by our statistical model in the current scope of the investigation. Future works could investigate relationships between factors and explore more advanced computational methods beyond global criterion optimisation methods, such as online multi-objective methods for Pareto optimal adaptation [24] that work for more specific contexts, including user movement [14].

11 Conclusion

In this work, we demonstrated a probabilistic approach to understanding user preference for adaptive placement of augmented reality interface that responds to changes in physical environments. We first conducted two studies through online crowdsourcing and in VR to collect data on user behaviour and preference in AR interface layout adaptation. By analysing the patterns of AR interface layouts created and adjusted by participants, we quantified the correlation between the perceived usefulness of widgets and their locations in the layout. We derived a set of potential factors behind user preferences for AR interface adaptation by assessing user-created layouts and analysing subjective user feedback. Building on this prior knowledge, we implemented a probabilistic optimisation system to generate adapted AR interfaces. Using generated layouts that prioritise different factors, we elicit posterior probabilities for their weighting coefficients in a utility function. We conducted a final user preference elicitation study through online crowdsourcing with a large sample size. Our results suggest that while users prefer adaptive AR interface placement results that prioritise factors related to the layout structures, the factors related to the geometry of the physical environment are prioritised less, whereas the semantic association between the AR interface and the environment only has a marginal effect on user preference of the adapted layouts.

Based on the data collected from this final study, we contribute a probabilistic model that predicts user preferences for different strategies for adaptive placement of AR interface in changing environments, while negotiating the trade-offs between different factors, for future AR interface layout adaptation systems to use as a prior model. Based on qualitative feedback from participants, we interpret user preferences and strategies from the prior model and distil concrete guidelines for future adaptive AR interface placement systems:

- ***Guideline 1: Adaptive AR interfaces should prioritise keeping virtual elements at similar and consistent distances from users.***
- ***Guideline 2: Adaptive AR interfaces should maintain a clear visual structure of the layout of the virtual elements by arranging them close to each other.***
- ***Guideline 3: Adaptive AR interfaces should take caution in defining and integrating factors related to user-perceived relationships between virtual elements and the physical environments as well as the objects in them.***

We open-source the probabilistic model and the data to enable future works to build on our findings and experiment with alternative analyses.

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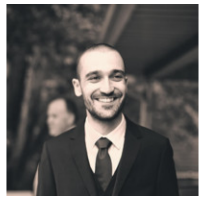

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