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STARE: Augmented Reality Data Visualization for Explainable Decision Support in Smart Environments

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ABSTRACT The Internet of Things (IoT) provides unprecedented opportunities for the access to and conflation of a myriad of heterogeneous data to support real-time decision-making within smart environments. Augmented Reality (AR) is on cusp of becoming mainstream and will allow for the ubiquitous visualization of IoT derived data. Such visualization will simultaneously permit the *cognitive and visual binding* of information to the physical object(s) to which they pertain. Important questions exist as to how one can efficiently filter, prioritize, determine relevance and adjudicate on individual information needs in support of real-time decision making. To this end, this paper proposes a novel AR decision support framework (*STARE*) to support immediate decisions within a smart environment by augmenting the user's focal objects with assemblies of semantically relevant IoT data and corresponding suggestions. In order to evaluate this technique, a remote user study was undertaken within a simulated smart home environment. The evaluation results demonstrate that the proposed Semantic Augmented Reality decision support framework leads to a reduction in information overloading and enhanced effectiveness, both in terms of IoT data interpretation and decision support.

INDEX TERMS Augmented reality, smart environment, decision support, semantic annotations, ubiquitous computing.

I. INTRODUCTION

Today's smart environments not only play a role in monitoring and task execution, but pointedly they also directly influence and serve to inform people's decision-making in undertaking routine daily activities [1]. The increasing dataset scales brought by the smart environment revolution however reveals the limitations of traditional 2D-screen-based smart environment data visualization interfaces [2]–[5]: decision-makers have to spend an additional cognitive load on searching and filtering valuable Internet of Things (IoT) data from the centralized long data lists.

The emergence of Augmented Reality (AR) techniques has brought in new potential decision-support solutions to spatially scatter these IoT data over a smart environment with the proximity to the data sources, such as Situated Visualization [6] and Situated Analytics [7]. However, such situated or in-situ visualization of scattered IoT data may sometimes lead to the separation between relevant data and the user's focus, thus generating inconsistencies. Also, possible redundancies can gradually accumulate when the decision-maker switches attention from their currently focused context to discover the relevant information among other irrelevant IoT data scattered over the smart environment. To avoid these possible redundant and inconsistent artifacts which contribute to information overload factors and hindered decision making [8], this paper proposes the *STARE* (SemanTic Augmented REality) decision support framework to augment the user's focal context with ubiquitous and seamless decision support. To achieve this seamless focus augmentation, *STARE* tracks the user's focus and establishes multi-dimensional semantic associations between the user's focal objects and relevant heterogeneous IoT data according to their semantic properties. Based on these semantic object-data associations, *STARE*

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can reflect on how the user's focal object can be affected by the relevant environmental changes through semantically annotating it with all relevant IoT data that can change the object's current state or affect decision making about it.

Decision support systems (DSS) is commonly defined as computer-based system used for assisting decision making [9]. Prior data-oriented AR smart environment DSS [10]–[16] demonstrated that they could assist in decision-making by providing data retrieval and information analysis [17] but left the vital decisions to expert users who are assumed to be equipped with enough professional knowledge. However, non-expert users may benefit more from the higher-level model-oriented decision support such as consequence simulation and suggestions [17] for non-vital decisions. Relevant literature search did not show such high-level decision support from prior AR smart environment interfaces. Therefore, utilizing the established semantic object-data associations and the focus augmented IoT data, *STARE* further encapsulates an ontology-based suggestion model to provide explainable suggestions targeted for non-expert users' focal decision contexts within a dynamically changing smart environment. For each type of focal object, multi-dimensional semantic data-object associations are dynamically constructed by the decision engine and a semantic annotator. Based on these semantic data-object associations, a type of focal object and its sub-types are semantically annotated with explainable decision support data that comprises the brief suggestions and relevant environmental changes as the explanations. By encapsulating a novel explainable suggestion model and the focus augmentation modality, *STARE* achieved significantly improved decision-support effectiveness and less perceived information overload when evaluated against prior common AR smart environment data visualization interfaces.

This paper makes the following novel contributions:

1) It delivers the first model-oriented AR smart environment decision support framework (*STARE*) that allows for semantic annotation for focal objects with explainable suggestions.
2) It illustrates a proof of concept prototype that provides decision support in a smart home using the proposed *STARE* framework.
3) Through the vehicle of a remote simulated Mixed Reality(MR) experiment, it benchmarks this proposed approach against a common AR in-situ IoT data visualization approach [11], [18] within a smart home decision-making context. Thus, the principal focus of the experiment is to explore the effects of the explainable suggestion model and the focus augmentation modality of *STARE*.

II. RELATED WORK

A. AR DECISION SUPPORT SYSTEMS IN SMART ENVIRONMENTS

The research about AR decision support in smart environments has emerged in recent years [10]–[16] as the popularization of IoT and AR technologies in people's daily life. According to Alter's Decision Support System (DSS) taxonomy [17], compared to these data-oriented DSS, model-oriented DSS utilizes a complex combination of decision rules, models, definitional relationships, and formulas to provide higher-level decision support. Although providing such higher-level decision support may benefit non-expert users more, the system requirements are even more challenging in a dynamically changing environment, which also has led to a research gap of the AR model-oriented DSS in a smart environment.

For AR smart environment DSS, one important challenge is how to filter and localize the heterogeneous IoT data at a relevant place and time for optimal decision support effect. AR in-situ visualization stressed spatial proximity between the data representation and the environment where the data is collected [18]–[24]; Situated Visualization and Embedded Visualization both stressed the alignments between the physical referents and the individual data representation or the entire visualization [25]. Following these AR visualization paradigms, many AR sensor data visualization interfaces overlayed situated or in-situ data over sensing instruments to allow for a more continuous user experience. However, for other decision-making contexts where these instruments are not always located close to the decision-involved objects, such in-situ or situated IoT data localization approaches may separate the relevant data and the investigated objects, thus leading to additional cognitive load.

Other novel approaches such as semantic filtering (or logical filtering [26]) have also been proposed to filter relevant information according to the predefined user preferences, user's current goals, user's focus, user's contextual feedback history, object's subjective properties, and environmental changes [26]–[31]. The semantic filtering approaches based upon users' current goals usually necessitate the explicit specification of a user's current task [26], [29]. The user's current location and focus were also tracked with Fiducial markers [27], GPS [28], semantic zooming [32], MagicLenses [33], [34], and cloud anchors [35]. On top of constructing persistent data-location associations, object classification was also applied to dynamically identify objects within the user's current focus [10], [18], [30], [31], [35], [36], among which tracking the user's focal object based on natural feature analysis allows for relevant data localization [10], [30] with less constraining knowledge [37]. In these past examples, there is a lack of association definition between heterogeneous IoT data and various object categories in a smart environment.

For decision support systems in a smart environment, another key challenge is how to combine static predefined decision rules and heterogeneous real-time updated IoT data to provide timely decision supports in dynamically changing environments. One common approach is to define a single data threshold for each type of environmental change collected by the IoT plants [13], [23] to give an alert for irregular environmental changes. However, different objects may require different thresholds to reflect how the data affect the object states and involved decisions even for the same type of IoT data. Accordingly, this paper proposes the first model-oriented smart home AR DSS to provide suggestions and explanations based on the semantic data-object associations.

B. AUGMENTED REALITY VIEW MANAGEMENT

As Bell *et al.* argued [38], AR view management requires locating related objects near each other or preventing occlusion. By attaching AR visual elements to the physical objects [39], spatial analytic interfaces are allowed to facilitate in situ spatial interactions with the AR data [40]. Similarly, Situated Analytics [7] argues that in situ AR data projection directly associates AR information with relevant physical objects, which were hereupon claimed to have enhanced decision-making. Also, numerous solutions have been explored to solve the AR visual clutter issues. Visual clutter, as the leading cause of occlusion and fragmentation of information [41], may make the AR display challenging to interpret and thus lead to high cognitive load. By remapping [42] and segregating [43] AR visual elements according to the attached objects' depth, or grouping the visual items using hierarchical clustering [44], or affecting users' visual attention with subtle cueing methods [45], several AR visual items may be sorted clearly for a better user experience. Inspired by these prior work, *STARE* avoids visual clutters by assembling and mapping relevant AR data to the associated objects with the focus augmentation modality.

C. AR ONTOLOGY

Prior work has applied ontologies to facilitate the context-awareness of AR systems by modeling an information-rich context [46]. Perera indicated that AR blended with ontologies provides a promising direction to map the relationship among situation perception, ubiquitous access, and natural interaction with the context [47]. Djordjevic *et al.* integrated a smart-home domain ontology with mobile AR devices to allow for energy consumption visualization [48]. Similar AR ontology-based information browsing interfaces visualized Point Of Interests (POIs) and historical events at cultural heritages [49]. Park *et al.* proposed a conceptual AR ontology-based system framework that integrated building information modeling (BIM) to assure construction data quality and accuracy [50]. Hervas *et al.* proposed an AR ontology system to support daily user needs through simple interactions with the environments [51]. Toro *et al.* further applied AR ontologies to support instant maintenance decisions [52] based on maintainers' past decisions. Based on the above prior work, this paper constructs the semantic associations between IoT data and smart home objects using a lightweight ontology, which aims to mitigate common DSS issues about the information overload [53] and user trust [54].

D. AR INTERFACE VALIDATION IN VIRTUAL SIMULATION ENVIRONMENT

AR interface validation usually confronts challenges about the in-situ evaluation within targeted physical contexts, while VR environments allow for immersive emulation of real-world application contexts with accurate control of experimental factors. Immersive VR environments thus have been exploited to conduct AR studies on AR item searching [55], AR registration error [56], virtuality/reality latency [57], AR agents [58], and smart home simulation [59]. By replicating the real-world AR experiments in simulated VR environments, comparable results were found [60], which has shown the feasibility of such a simulation AR study approach. Such Mixed Reality (MR) simulated experiments also showed their promise for smart environment evaluation [59]. However, the differences between reality and the computer-generated world have also led to several limitations, which include the evaluation of AR interfaces that require frequent interactions with physical objects as well as outdoor light and tracking issues which can be challenging to simulate [56], [61]. The AR smart home interface evaluated in this paper does not require necessary tactile interactions with physical objects, and it is designed for small-sized indoor environments. Also, the repeated measure comparison experiment may minimize the potential bias caused by these confounding factors of the simulation settings.

E. REMOTE EXPERIMENTS

Common user studies require in-lab participation and supervision, thus are expensive and inconvenient for day-to-day evaluation [62]. Remote user study methodologies have been proposed to enable large-scale behavioral studies [62]. For the experiments requiring dedicated equipment or specific experiment context, Virtual Reality has been exploited to simulate the workbench for tele-education and collaborative work [63]–[67]. Although no prior work has been found to evaluate the AR interfaces using VR simulated environment, these prior works still indicate such feasibility, which shows necessities under COVID-19 when close contact was impossible. Following the principles provided by similar studies, this paper illustrates this first attempt and gives further guidelines.

III. SYSTEM OVERVIEW

By implementing *STARE* on a Microsoft HoloLens, this proof of concept system encapsulates the focus augmentation and a novel explainable suggestion model to shorten the physical and semantic distance between the user's focal object and its relevant decision support data. The following system overview has been summarised before in a prior work [68]. However, this paper gives a more expansive description of each of the components that make up the *STARE* approach.

A lightweight ontology annotates the focal objects with a semantic annotator. The decision engine further creates multi-dimensional semantic associations between the annotated object and its relevant IoT data. From these associations, the system can instantly augment the decision-maker's focal object with an assembly of relevant IoT data and corresponding brief suggestions. This mechanism allows the users to freely explore the smart environment by invoking

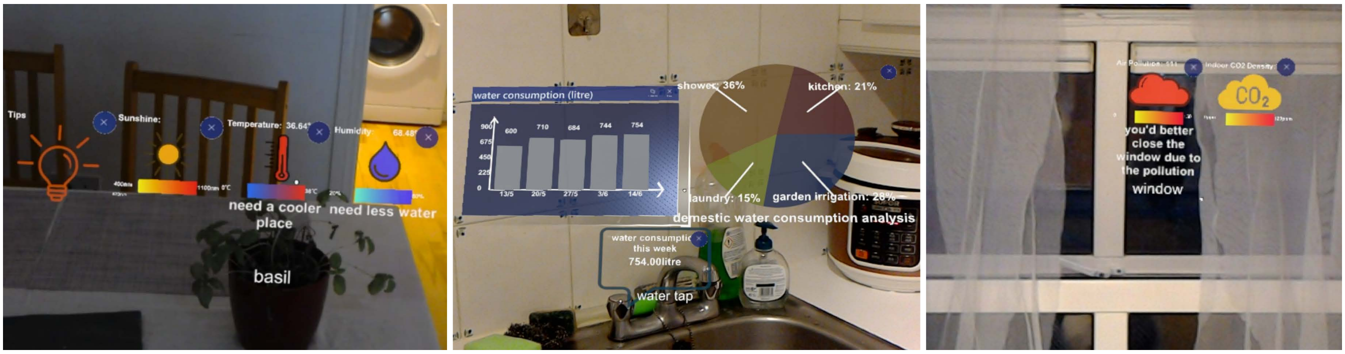

FIGURE 1. Augment physical objects with all relevant IoT data and corresponding brief suggestions for instant explainable decision support.

the decision-support information for the objects they are currently focused on. For example, a user wants to open the window but is not sure about outdoor air quality, so they use a voice command to trigger a decision-support AR annotation about the window, which superimposes indoor and outdoor air quality data over the windows and shows a suggestion to close the window due to outdoor air pollution (Fig. 1).

A. SYSTEM ARCHITECTURE

As is illustrated in Fig. 2, this system consists of five main modules: object classifier, semantic annotator, decision support component, Bluetooth sensor data scanner, and AR information visualization module. To achieve the focus augmentation strategy, the system applies *focus+voice command* modality to allow for the hands-free triggering of the AR information over objects within the user's focus. When the voice command is detected, the cloud object classifier recognizes the objects within the user's focus and passes the object label to the semantic annotator for object annotation and localization. Next, the decision support module constructs the semantic associations between this object and its relevant IoT data to generate a semantic model for this focal object. This system then passes the model to the AR front-end to generate suggestions and explanations. The system then inputted the BEACON IDs of relevant IoT data associated with the focal objects to the Bluetooth Low Energy (BLE) sensor data scanner to filter the relevant IoT data streams fed to the information visualization module. Finally, using the semantic models created by the decision support component, the AR front-end superimposes the focal object with its semantically relevant IoT data and corresponding suggestions to provide instant-explainable decision support.

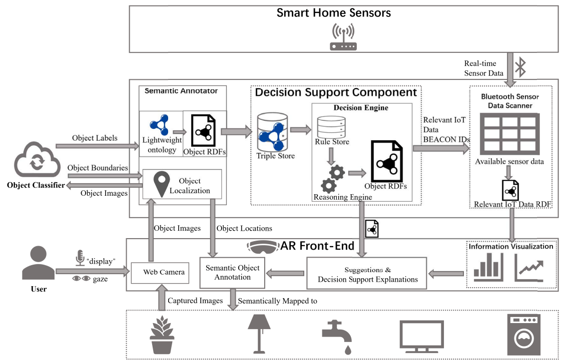

FIGURE 2. System architecture diagram: the system consists of five main modules: object classifier, semantic annotator, decision support component, Bluetooth sensor data scanner, and AR information visualization module. To achieve the focus augmentation, the *focus + voice command* interaction approach is applied to allow for the active triggering of the AR information for focal objects using a voice command.

B. OBJECT CLASSIFIER

This system classifies objects through image analysis. The web camera captures an image for analysis after detecting the voice command. This image is then sent to the Microsoft Azure Custom Vision[1] cloud service for object classification. As recognizing all objects in the smart environment and superimposing information over them will lead to information overload, an object list was defined for each given smart home context to filter only decision-involved objects. Moreover, one matching percentage threshold and object depth threshold are also defined to filter out the unclear objects. For each matching object successfully recognized from this image, the object classifier returns one bounding box, which is then used for object localization in the physical world. This decision-involved object list can be modified or extended by removing or adding object images for training.

C. LIGHTWEIGHT ONTOLOGY & SEMANTIC ANNOTATOR

The proposed lightweight ontology aims at providing a semantic structure for the data collected from the different sensors and serves as a stepping stone towards the more elaborated reasoning rules of the Decision Support component of *STARE*. By extending the Semantic Sensor Network (SSN) Ontology,[2] each node provides a formal expression of the

[1]https://azure.microsoft.com/en-us/services/cognitive-services/custom-vision-service/

[2]https://www.w3.org/TR/vocab-ssn/

events captured by the sensors. The semantic annotator extends the SOSA Ontology (Sensor, Observation, Sample, and Actuator) [69] to formally express and record the object recognition events captured by the object classifier. Utilizing an object boundary acquired by the object classifier and the object depth, the semantic annotator is allowed to precisely localize the object in the physical world and initiates an annotation for this focal object. Simultaneously, the *STARE* lightweight ontology transfers the object label recognized by the object classifier into Resource Description Framework (RDF) documents (Fig. 2), which ensure that the label structures comply with the semantic data models thus can be easily consumed by the decision support component. The *STARE* lightweight ontology further supports observations registered by the sensors and provides a semantic structure of the sensors by combining the vocabularies from SSN and SOSA.

D. DECISION SUPPORT COMPONENT

The core of the *STARE* framework is a decision support component that provides a novel suggestion model to achieve high-level decision support within a dynamically changing environment. As Fig. 2 shows, the decision support component incorporates a triplestore and a decision engine to generate suggestions and explanations. The object RDF documents generated by the semantic annotator are all stored in this triplestore, which serves as the repository to feed the decision engine. This decision engine comprises a rule store and a reasoning engine to construct the multi-dimensional semantic associations between the object and its relevant IoT data. The rule store assigns decision rules to the object RDF, while the reasoning engine makes logical inferences based on the object's decision rules. In the rule store, general decision rules are defined for several object superclasses to indicate the optimal decision principles under different smart environment conditions, based on which the specific decision rules of object subclasses are further derived. These decision rules are now defined by system designers at this stage, while they can also be defined by domain experts in the given decision area or be customized by end-users with a customization component in the future. According to the decision rules, the reasoning engine semantically annotates this object RDF document with a list of relevant IoT data and their descriptors. As Fig. 3 illustrates, this relevant IoT data list contains all environmental parameters that may change the object's states (e.g. sunshine and moisture for indoor plants; fridge temperature for the fridge, etc.) or interfere with the usage decision about this object (e.g. air quality for air purifier and windows; energy consumption for the home appliances, etc.). Such a semantic data-object association mechanism can be applied to various smart environments as it considers heterogeneous data types and objects types.

Each type of semantically associated IoT data is also semantically annotated using the *STARE* lightweight ontology. For each semantically annotated IoT data, the data descriptor contains the objective properties, such as the sensor/device name and a BEACON ID used for BLE data scanning (Fig. 2). IoT data descriptors also contain decision-involved properties to support dynamic suggestion generation, which includes decision-required thresholds of this IoT data and recommended actions for its associated objects. For example, indoor plants are semantically associated with soil moisture sensors, whose decision-involved properties can contain the optimal moisture range under the current plant growth stage and sunshine level. Based on these properties, the recommended watering actions are predefined for the sensor observations that moisture is lower than this optimal range. These decision-involved properties reflect how the moisture sensor data can change the indoor plants' health states, thus affecting the watering decisions, therefore are defined in the descriptors of the moisture sensor data associated with the indoor plants (Fig. 3). Following the decision rules defined for the indoor plants, basil and roses will be assigned with the same type of relevant IoT data but with slightly different descriptors according to their different growth conditions. Hence, under any certain condition reported by this list of IoT data, the reasoning engine can find abnormal IoT data that falls into its decision-required thresholds, and infer the logical consequences about the object's state changes or usage requirements, thus generating suggestions based on their descriptors(Fig. 3). However, due to the interrelationships and interference among different object properties, object RDF documents are needed to formally express and record these different object properties and their inner connections. Therefore, the object RDF documents that the decision engine has further semantically annotated are then passed to the AR front-end to enable decision support data visualization. Simultaneously, the relevant IoT data list associated with this object RDF is also passed to the BLE sensor data scanner, which scans all neighborhood sensor data streams. Accordingly, the BLE scanner filters relevant IoT data with the matching BEACON IDs from all real-time sensor data streams. Then it encapsulates the current values of these relevant IoT data into RDF documents to feed the AR information visualization module.

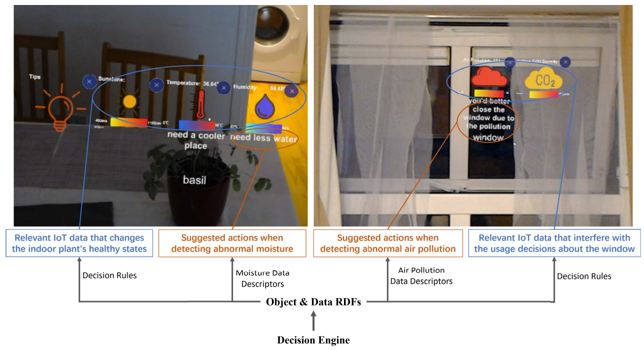

FIGURE 3. Decision engine provides decision rules and IoT data descriptors for explainable decision support data visualization.

FIGURE 4. VR simulation experiment platform (left: *interface A*: smart home interface applying the *STARE* framework; middle: *interface B*: smart home interface applying the suggestion model of the *STARE* framework without focus augmentation; right: *interface C*: a common smart home interface which in-situ visualizes all sensor data).

E. AR EXPLAINABLE DECISION SUPPORT DATA VISUALIZATION

As Fig. 3 illustrates, utilizing the decision rules and IoT data descriptors derived from the STARE lightweight ontology, the AR front-end can superimpose suggestions over the focal object to support decisions about it. However, such high-level suggestions or recommendations without any explanation do not generate trust from a decision-maker. Nunes and Jannach [54] indicated that explanations could provide more information about the interrelation among relevant entities in the knowledge base to help the decision-maker better understand and trust the provided suggestions or recommendations. Accordingly, *STARE* explains the provided brief suggestions with an assembly of semantically relevant IoT data (Fig. 3) as the decisive input values that are used to determine the resulting advice [54].

For a decision to be generated, input values must reach the decision-required thresholds; once this is achieved, the key features within that decision are then highlighted with high color codes and alerts (Fig. 3). Hereupon, the AR information visualization module real-time superimposes all decisive input values over the object's semantic annotation to clearly explain the decision logic behind the suggestions. Such explainable decision support not only helps the user to trust and learn from the illustrated decision logic (e.g. with what air quality should they turn on the air purifier), but also provides them with more freedom to make their own decisions based on the visualized IoT data and the decision logic they learned from the prior user experience.

In prior work that used in-situ or situated visualized IoT data with AR headsets, the situated information is typically transferred into text [35], color values [70], shape sizes [71], transparency [23], height [71], gauges [20] to allow for effortless comprehension, while detailed information is normally considered less important. To retain these details without causing visual clutter, this system provides a simplification for all superimposed data and allows for further investigation utilizing the concept of details-on-demand [72] when this simplification is insufficient for the user. As Figure 1 shows, one data icon was used to represent each IoT data type and its color was mapped to the corresponding value. The IoT data value and data name are also displayed above the icon for precise data reading [20], [23]. By clicking (gesture interaction) on any IoT data annotation, detailed information will be visualized in the form of line charts, histograms, or pie charts, which are determined by the data types.

Moreover, customized display preference (Fig. 2) of each semantic data-object association is also recorded in the descriptors according to a user's historical interactions with the system. In practice using historical interactions, the user can remove any superimposed IoT data annotation over any object, and this data will not be displayed for this object in the future.

F. IMPLEMENTATION

This system was developed using Unity3D,[3] and the Microsoft Hololens[4] was used for the proof of concept interface development. The Unity3D plugin Mixed Reality Toolkit[5] provided the basic support for MR interface development. Microsoft Azure Custom Vision[6] cloud service was applied for object classification. For the remote experiment, the simulated VR smart home and smart home interfaces were developed with SteamVR.[7] The Unity3D plugin Http Client[8] was applied to upload experimental data to an online database. Due to the potential risk of VR symptoms [73], it was declared on the participant recruitment poster that the computer used to conduct the experiment tasks must be equipped with a minimum graphics card requirements of GTX 1060 or RX 480.

IV. REMOTE USER STUDY WITH MIXED REALITY SIMULATION

It is expensive and time-consuming to construct a fully equipped smart environment for evaluation. Additionally, the user study would potentially require close contact between the participant and experimenter, which is impossible during

[3]https://unity.com/
[4]microsoft.com/en-us/hololens
[5]https://docs.microsoft.com/en-us/windows/mixed-reality/mrtk-getting-started
[6]https://azure.microsoft.com/en-us/services/cognitive-services/custom-vision-service/
[7]https://store.steampowered.com/steamvr
[8]https://assetstore.unity.com/packages/tools/network/http-client-79343

the COVID-19 crisis. Therefore, a remote user study was used to compare the designed AR smart home interface with two alternative interfaces in a virtual smart home (Figure 4). This study allowed the remote participants to experience the AR smart home interfaces within an immersive simulated context using their Virtual Reality headsets. Quantitative experiment results, including participants' movements, answers, and questionnaire feedback, were automatically collected and uploaded to an online database from the remote simulated VR experiment testbed.

STARE encapsulates two strategies to improve the decision maker's user experience. Firstly, the focus augmentation allows users to trigger the AR decision support service for their focal object, which is achieved by the *focus + voice command* modality in the proof of concept interface. Secondly, the proposed explainable suggestion model assembles object-data associations to provide direct-immediate decision support within smart environments. To clearly evaluate the benefits and limitations of these two strategies in *STARE*, the work listed six research questions to explore the effects of the proposed suggestion model and the *focus + voice command* modality (Table 1). To evaluate the explainable *STARE* suggestion model, this proof of concept interface was compared against an alternative interface, which used the most common in-situ IoT data visualization metaphor [11], [18] to provide data-oriented decision support in a smart environment. Additionally, to evaluate how the application of focus augmentation affected the user experience, a proof of concept interface was compared against another alternative interface that applied the same suggestion model but without the focus augmentation. By comparing against these two alternative smart home interfaces, the benefit and limitation of the two main strategies applied in the *STARE* can be clearly evaluated.

Therefore, three smart home interfaces were compared:

- *Interface A:* the proof of concept interface that applies to *STARE*, which cooperates the focus augmentation (*focus + voice command* interaction modality) and a novel suggestion model to provide decision support (Figure 4, left).
- *Interface B:* a smart home AR interface that applies to *STARE* while not applying *focus+voice command* interaction modality to augment focus. Instead, it displays all AR information over relevant objects at once from the beginning (Figure 4, middle).
- *Interface C:* A common AR in-situ smart home data visualization interface [11], [18] that directly superimposes all sensor data over corresponding sensors at once (Fig. 4, right). As this data-oriented decision support interface did not directly provide suggestions, extra information, such as decision rules, is provided to help participants complete the tasks (Subsection IV-C1).

As a prior MR simulation user study ([74]) suggested to "avoid the introduction of unwanted between-subject variables", so a within-subject experiment was designed and conducted to compare these three interfaces. The order of these three test conditions was counterbalanced between participants to mitigate the transfer effect. As Table 1 shows, by comparing these three smart home AR interfaces, six research questions were explored from the aspect of effectiveness, user satisfaction, and information overload of the proposed suggestion model and its cooperation with focus augmentation strategy. To quantitatively answer the research questions about the effectiveness, the main experimental task required the participants to answer questions about the smart environment with the aids of different given interfaces. In this way, the error rate and task completion time could quantitatively reflect how the tested interfaces help users understand the smart environment and make correct decisions from different aspects.

A. HYPOTHESES AND EXPERIMENTAL VARIABLES

As explained above, the only independent variable was the smart home interface, and it had three test conditions: *interface A*, *interface B*, *interface C*. This common in-situ IoT data visualization interface *interface C* was regarded as the baseline condition. Both objective measures and subjective feedback were collected as dependent variables. To answer the research effectiveness question, the testbed collected the task completion time and error rate as the objective indications of the system effectiveness. Subject ratings about the effectiveness were also collected to check if they coincide with the objective measures. To answer the other four research questions, the testbed collected subjective ratings from a questionnaire to measure the information overload and user satisfaction. Based on these experimental variables, apart from the null hypothesis, six hypotheses are listed in Table 1 to answer the corresponding research questions on the left.

H0 There is no difference between the three tested AR smart home decision support interfaces.

B. REMOTE PARTICIPANTS

Participant recruitment advertisements were posted in Facebook groups to recruit remote participants over 18 and had access to a VR headset and a computer at home. 26 people sent the request to participate in the remote experiment, among which 3 of them did not meet the equipment requirements, and 5 of them did not complete the experiment. Therefore, experimental data was collected from 18 participants. All these 18 participants had prior experiences in using Virtual Reality products. 7 participants had prior experiences using Augmented Reality products.

C. EXPERIMENTAL PROCEDURE

After the participants signed the consent forms, the instruction documents and the simulation experiment testbed were sent to the participants. After finishing the before-task training provided by the simulated experiment testbed, each participant performed three experimental tasks using the three smart home interfaces in counterbalanced orders. Each participant was asked to fill in a questionnaire about each interface separately, and they did this immediately after they

TABLE 1. Research questions (left), corresponding hypothesis (middle), and corresponding results (right).

Q_1: How does the suggestion model of *STARE* affect the user's understanding and decision-making about the smart environment?	H_1: the suggestion model of *STARE* leads to better effectiveness than the AR in-situ IoT data visualization in the context of a smart home.	**Supported**
Q_2: How does the suggestion model of *STARE* affect user satisfaction about a given smart environment AR interface?	H_2: the suggestion model of *STARE* leads to better user satisfaction than the AR in-situ IoT data visualization in the context of a smart home.	Rejected
Q_3: How does the suggestion model of *STARE* affect perceived feelings of information overload caused by the smart environment AR interface?	H_3: the suggestion model of *STARE* causes less information overload than the AR in-situ IoT data visualization in the context of a smart home.	Rejected
Q_4: When applying the *STARE*, how does the $focus + voice\ command$ focus augmentation affect the user's understanding and decision making about the smart environment?	H_4: The applying of $focus + voice\ command$ focus augmentation leads to better effectiveness for the the *STARE* in the context of a smart home.	Rejected
Q_5: How does the $focus{+}voicecommand$ focus augmentation affect the user's perceived feelings of *STARE*?	H_5: The applying of $focus + voice\ command$ focus augmentation leads to to better user satisfaction for *STARE* in the context of a smart home.	Rejected
Q_6: How the $focus + voice\ command$ focus augmentation affect perceived feelings of information overload caused by *STARE*?	H_6: The applying of $focus + voice\ command$ focus augmentation causes less information overload for *STARE* in the context of a smart home.	**Supported**

finished a given task. Instead of supervising the experiment tasks by arranging the online meetings between remote participants and experimenters, an automatic experiment process navigation and supervision component was developed for the VR smart home testbed (Subsection IV-D). This autonomy is crucial for the experiment as it reduces the potential for experimenter bias [75]. This bias can be caused by experimenters' expectancy effects [75] when the experimenters are fully engaged in the whole task procedure for either supervision or guidance aims. Virtual and Augmented Reality technology could be particularly vulnerable due to the novelty of the technology to a participant. Past simulated experiments have even gone as far as using dedicated agent systems [58] along with the corresponding avatar to give their testbed autonomy to conduct the whole experiment without the need of input from the experimenter. In this case, the UI itself was sufficient to guide the participants, and given the tracking data from the resulting experiment, this proved to be the case. Only two outliers were discovered when this data was analyzed. Finally, this approach was taken to avoid the psychological pressure on the participants: the experimental tasks required no time limits to encourage participants to carefully answer the in-task questions, while when experimenters are staying in the online meetings to wait for the participants to finish each task, the participants may fail to answer in-task questions calmly and carefully out of the time pressure. This experimental procedure would not have been different, even if an in-person experiment was possible.

1) TASKS

For a remote user study that assumes no supervision and guidance from experimenters, the experiment tasks were simplified, making no requirements for any long text input or complex data manipulation. Therefore, each task only required the participant to answer 13 multiple choice questions with the assistance of a given interface. Four types of questions were designed to test the effectiveness of the given interface (Table 2) from the aspects of decision support or smart home information interpretation. Each question targeted one object and one or more types of IoT data that are accessible through the smart home interface, thus the participant needed to explore the virtual smart home with the assistance of the interface to be able to answer each question.

The orders of the within-task questions were counterbalanced to mitigate the transfer effect, and the same number of these four types of questions were provided for each task to keep the consistent difficulty. In addition, in each task, one extra question was inserted to detect contradictory answers, and this technique also allowed us to invalidate any user questionnaire result. While after checking the questionnaire responses, no responses were discarded as all remote participants answered these additional questions correctly.

As *Interface C* did not provide any brief suggestions like the other two interfaces, two extra charts containing the indoor plants' optimal growth conditions and home appliances' information were provided as extra decision-support information to enable the participant to finish the *interface C* task. These extra charts were also applied to simulate the common application scenario of such AR in-situ IoT data visualization interfaces which the user may need to search online for extra relevant information to make decisions according to the superimposed IoT data in the smart environment.

2) QUESTIONNAIRES

Each questionnaire consisted of three parts to measure system effectiveness, user satisfaction, and information overload. For each part of a questionnaire, 3 or 4 statements were listed to collect responses on 5-point Likert scales from *'not at all'* to *'extremely agree'*. Similarly, cross-checking questions were inserted to test the validity of the questionnaire answers (APPENDIX A Table 3).

TABLE 2. The within-task questions were designed to evaluate the interface effectiveness in terms of the decision support and smart home information interpretation.

Question Example	Targeted IoT data type	Evaluation goal
Do you need to turn on the cooker hood for now?	Indoor smoke density	Decision support
What can you do for now to make the lucky bamboo grow better?	Soil moisture; sunshine exposure; temperature	Decision support
What is the hourly energy cost of the radiator?	Radiator energy cost	Interpretation
What uses the most water in your home?	Water consumption statistics	Interpretation

D. VR SIMULATION REMOTE TESTBED

The testbed provided a medium-fidelity VR smart home as the experiment environment. Four indoor plants, nine types of home appliances, and thirteen smart home sensors were placed within this virtual home. Smart home applications normally assumed the users were familiar enough with the application environment, while this was hard to achieve for the simulated smart home in a short time. To make sure the participants knew where each object was placed in the virtual smart home, this testbed attaches a name label to each indoor plant or home appliance. This testbed also simulates the three tested smart home interfaces within the virtual smart home (Figure 4). Except for the usage of the proposed suggestion model and focus augmentation modality, all user interface designs of these three simulated interfaces were identical and strictly aligned with the actual proof of concept AR interface.

Apart from the simulated AR interfaces and the virtual smart home, this testbed was also embedded with the automatic experimental navigation and supervision services to guarantee the experiment's integrity. The experiment's integrity was also protected using a built-in automatic data collection module that collected and uploaded accurate experimental data, including heat maps of a user's movement during the experiment. Users were informed of this anonymous automatic data collection through the consent forms for the experiment.

1) AUTOMATIC EXPERIMENT PROCESS NAVIGATION AND SUPERVISION

As it was explained in Subsection. IV-C, automatic built-in experiment navigation and supervision were developed for the VR testbed to automatically guide the experiment procedure without biasing the experimental results. To achieve this goal, the testbed provided extra guidance information throughout the whole experiment process, which included an overall training, before-task warm-up, within-task question answering (Figure 4, left), after-task instruction, and extra authentication steps to guarantee the correct experiment procedure.

For the first time when the participant opened the VR testbed, an overall training phase was provided. This training phase ensured that the participant felt confident to use the smart home interface before each experimental task started. After this overall training, every time the participants began to use a new test interface, a before-task warm-up phase was provided to guide the participant to practice the interaction with this interface. As Figure 4 (left) shows, to avoid distracting the participant from the immersive experiment context, all within-task questions were displayed and answered within the VR testbed. After each task was finished, the after-task instructions asked the participant to have a break and fill in the correct questionnaire before starting the next task. To guarantee that the participant fills in the correct questionnaire before starting the next task, the testbed required the participant to input the correct authentication code provided by the last questionnaire to start the next task.

2) AUTOMATIC EXPERIMENTAL DATA COLLECTION

All quantitative experiment data was collected automatically within this remote VR testbed in real-time and was uploaded to an online database after all experimental tasks were finished. Apart from task completion time, error rate, participant's assigned id, and task completion order were recorded, extra data was also collected to help replicate the participants' within-task behaviors. This extra data included the number of removed IoT data annotations, the number of voice commands triggered by the participants, and the participant's movement routine within the virtual smart home. By checking the participants' movement routine and the time they spent in each place, the experimenters can identify if potential distractions happened during the tasks.

V. RESULTS

In this section, the study results with statistical analyses ($\alpha = .05$, unless noted otherwise) are reported. Mauchly's Test was conducted before each ANOVA analysis and showed no violation to the Sphericity of the data.

A. EFFECTIVENESS

1) TASK COMPLETION TIME

As the task completion time box chart in Figure 5 illustrated, on average, participants took the longest time to complete the tasks using interface C, and took the shortest time to complete the tasks using interface A. A Shapiro-Wilk test found some of the conditions were not following a normal distribution, so the Align Rank Transform (ART) ([76]) was applied before conducting a Repeated-Measures one-way ANOVA for factorial analysis. After the ART, the outliers in the task completion time box chart (Figure 5) disappeared ([77]). The ANOVA result showed the significant main effect of the tested smart home interface ($F(2, 17) = 11.479$,

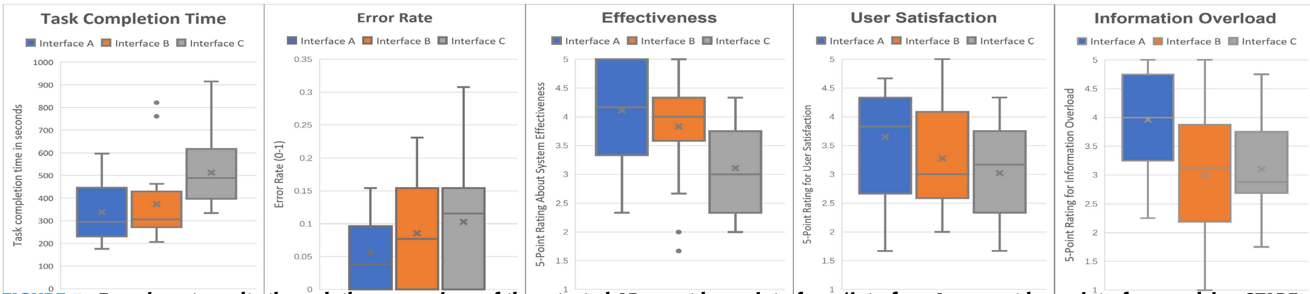

FIGURE 5. Experiment results through the comparison of three tested AR smart home interfaces(*interface A*: a smart home interface applying *STARE*, *interface B*: a smart home interface applying the suggestion model of *STARE* without focus augmentation, *interface C*: a common smart home interface which in-situ visualize all sensor data).

$p = .00016$). Thus the Null hypothesis *H0* was rejected. Further post hoc tests using the Bonferroni corrected t-tests revealed significant differences between *interface A* and *interface C* ($p = .000239$) as well as between *interface B* and *interface C* ($p = .00053$). No significant differences were found across the task completion time using *interface A* and *interface B*.

2) ERROR RATE

The error rate was calculated as the ratio of the wrongly answered questions over the total number of questions provided in each task. Overall, the error rates of all tasks were low and at most 2 errors were made within one task (the highest error rate was 0.15 and there were 13 questions for each task). As the error rate box chart in Figure 5 showed, averagely, participants made the least errors while using *interface A* and made the most errors while using *interface C*. However, using a Repeated-Measures one-way ANOVA with ART ([76]), no significant differences across the error rates under the three test conditions ($F(2, 17) = 1.172$, $p = .322$).

3) CORRELATIONS BETWEEN TASK COMPLETION TIME AND ERROR RATE

A Kendall's Tau-b test was performed to test the relationships between the task completion time and error rate for each test condition among the 18 participants. Positive correlations were found between these two dependent variables for all the three test conditions, and the correlation between the task completion time and the error rate under the condition of *interface A* was statistically significant ($t_b = .442$, $p = .0223$). This correlation is discussed in section VI-D.

4) RATE OF THE CORRECT SCORE

To get an integrated objective measure of the effectiveness, the Rate of the Correct Score (RCS) ([78]) was calculated for each tested interface, which has been used to *"transforming and combining response time and response accuracy variables"* to *"represent an index of response speed adjusted for errors"* ([78]). The combined results showed that the *interface C* led to the lower effectiveness ($RCS = .0228$) than the others: *interface A* ($RCS = .0364$) and *interface B* ($RCS = .0319$).

5) SUBJECTIVE RATINGS ON EFFECTIVENESS

The subjective ratings of the system effectiveness were measured with the average scores of the responses from the corresponding part of the questionnaires. The average score of the effectiveness rating about the *interface C* was the lowest (effectiveness analysis in Figure 5). The result of a Repeated-Measures one-way ANOVA with ART ([76]) also indicated significant differences across the effectiveness of three test conditions. Post hoc tests using the Bonferroni corrected t-tests showed that the *interface C* was significantly less preferred than the other interfaces: *interface A* ($p = .006$) and *interface B* ($p = .013$). No significant difference was found between the *interface A* and *interface B*. Therefore, the subjective rating on the interface effectiveness showed the significant main effect that coincided with the objective measure of task completion time: the *interface C* was the least effective among three tested interfaces. Thus the hypotheses H_1 was supported according to the significant improvement of *Interface A* and *Interface B* in terms of task completion time, RCS, and effectiveness ratings. While the hypotheses H_4 was rejected as no significant differences were found between *interface A* and *interface B* in terms of decision-support effectiveness.

B. USER SATISFACTION

The user satisfaction was measured with the average scores of the responses from the corresponding part of the questionnaires. As Figure 5 illustrated, the *interface A* had the highest average satisfaction score. However, a Repeated-Measures one-way ANOVA with ART ([76]) showed no significant differences ($F(2, 17) = 2.591, p = .09$) across the satisfaction ratings of the three tested interfaces. Thus hypotheses H_2 and H_5 were both rejected.

C. INFORMATION OVERLOAD

The information overload was measured with the average scores of the responses from the corresponding part of the questionnaires. From the average rating scores, participants perceived the least information overload from the *interface A* and perceived the most information overload from the *interface C*. By performing a Repeated-Measures one-way ANOVA, a significant main effect was found across the three tested interfaces ($F(2, 17) = 5.518, p = .008$). The further pairwise sample t-tests with Bonferroni correction showed significant differences in favor of *interface A* when compared to the others: *interface B* ($p = .015$) and *interface C* ($p = .0057$). No significant difference was shown between the *interface B* and *interface C*. The result strongly supported hypotheses H_6 while rejected hypotheses H_3.

D. CORRELATION BETWEEN INFORMATION OVERLOAD AND EFFECTIVENESS

The Kendall's Tau-b test was performed between the information overload and effectiveness ratings, significant positive correlations were shown across all measures of these two variables for *interface A* and *interface B*. Significant positive correlations were found between the information overload and objective measures of effectiveness for *interface C*.

VI. DISCUSSION

By comparing three different smart home decision support interfaces, this user study evaluated the explainable suggestion model and the focus augmentation modality of *STARE* in terms of effectiveness, satisfaction, and information overload. By supporting the hypothesis H_1 while rejecting the hypothesis H_4, these results showed that the suggestion model helped improve effectiveness, while the *focus + voice command* focus augmentation modality did not bring higher effectiveness. By supporting the hypothesis H_6 and rejecting the hypothesis H_3, these results proved that by applying the focus augmentation modality, *STARE* achieved less information overload. No improvement in user satisfaction was observed from the results as hypotheses H_2 and H_5 were both rejected.

A. USER SATISFACTION

The technique did not lead to significant improvements in terms of user satisfaction. As mentioned in section III, the focus augmentation modality shortens the distance between the user's focal object and its relevant decision support data. Thus the users do not need to approach the data sources to read the required information. However, as the experiment was conducted in a virtual world that allowed for instant navigation, this shortened distance provided by the focus augmentation modality may not have been noticed by the users even if the quantitative data showed that they took substantially less time using the *interface A* and *interface B*. Also, the in-task questions' complexity was not high enough to lead to significant differences in user satisfaction and error rate.

B. INFORMATION OVERLOAD

The results showed that *STARE* significantly mitigated the information overload issue by applying the focus augmentation modality to trigger the decision support data for focal objects. Regarding the highest ratings of *interface A* in terms of information overload, one possible reason might be that it displayed the least amount of information at any given time. The *focus + voice commands* modality helped reduce the amount of displayed information: all data irrelevant to the object within the participant's focus are hidden.

Without the application of the focus augmentation modality, *STARE* did not lead to the significant decrease of perceived information overload so the hypotheses H_3 was rejected. This result proved that simply augmenting all smart environment objects with decision support data will lead to duplication.

However, interestingly even though such duplication increased the total amount of information displayed by the *interface B*, the *interface B* still showed slightly lower perceived information overload compared to the *interface C* which displayed much less information (information overload analysis in Figure 5). This result indicated that the possible duplication caused by the suggestion model of *STARE* was less important compared to the advantages of the reduced distraction brought by the focus augmentation modality. Moreover, although *interface C* displayed the least amount of information within the user's field of view among the three tested interfaces, it still led to the highest perceived information overload. This surprising result might have suggested that *interface A* led to the least perceived information overload not only due to the reduced amount of information, but also, the superimposition of the decisive input data assembly over the decision-involved objects led to less cognitive load for the user compared to the scattered in-situ superimposition of sensor data. Therefore, the focus augmented within *STARE* although displays more information within the user's field of view compared to the common approach of in-situ sensor data superimposing, still leads to less perceived information overload by allowing for a proactive trigger of decision support data over the focal objects.

The positive correlation between the effectiveness measures and the information overload ratings showed that the information overload perceived by the participants could have affected their decision performance. The increased amount of displayed information within the user's field of view, as well as the distraction of scattered irrelevant information, might have both led to more extra time and effort spent on searching for useful information.

C. EFFECTIVENESS

The results illustrated in section V-A1 indicated that the *STARE* suggestion model led to the highest efficiency. Interestingly, the close results achieved by *interface A* and *interface B* in task completion time (Figure 5) have shown that the usage of *focus + voice command* focus augmentation modality did not lead to longer decision-making time, although it as the extra step to proactively trigger information display usually takes extra interface interaction time. This surprising result shows that participants spent longer time on searching and filtering helpful information to support decision making than proactively triggering the information

TABLE 3. Post task questionnaire A.

Measured Dependent Variable	Questions
Effectiveness	This system is easy to use. The visual design of the system is unclear.. I can find the necessary information using this system.
User Satisfaction	This system helps me to easily answer the questions within the task. I prefer using the voice command to display information. This system is beneficial for my use. Please select A for this question
Information Overload	This system provides too much information. This system provides the right amount of information. This system provides information that distracts me. The system provides information without any clutter.

display for decision-involved objects. Therefore, reducing distractions caused by information redundancies could be more important than simplifying interface interactions regarding decision efficiency improvement.

The hypotheses H_1 was supported according to the significant improvement of *Interface A* and *Interface B* in terms of task completion time, RCS, and effectiveness ratings. However, despite the significantly improved decision efficiency achieved by the proposed suggestion model, the results illustrated in section V-A2 indicate that the suggestion model did not make significant improvements on the decision accuracy. As section V-A2 showed, although this suggestion model did slightly reduce the error rates, the error rates under all test conditions were meager. This result might indicate that the designed questions within the tasks were not difficult enough to cause errors. Thus, the participants could still find the correct answers using any smart home interface even though it might take longer to use certain interfaces. On the other hand, the overall low error rate also shows that the automatic supervision and guidance worked well to assist the smooth task procedures.

D. LIMITATIONS

The remote MR study allowed for a user study during COVID-19. Meanwhile, the outliers in task completion time analysis of Figure 5, as well as the movement heat map collected from the VR testbed, indicated potential distractions during the task procedures. This distraction was hard to avoid without the close supervision of experimenters. However, thanks to the automatic experiment supervision and navigation feature of the VR testbed, such situations were very few and did not lead to significant bias to the results. Additionally, the positive correlation between the task completion time and the error rate of the *interface A* might indicate that some participants did not get fully trained by the warm-up phases before the tasks thus needed to check the introduction document during the task. The reason behind this assumption is that *Interface A* required the additional use of voice command interaction, which was an additional modality that a participant needed to remember. These limitations will be easily mitigated in a future physical user study using the AR smart home interfaces with physical smart home settings to compare these results.

VII. CONCLUSION

This paper has presented an innovative AR smart environment decision support framework (*STARE*) which incorporates a novel suggestion model and a focus augmentation modality to allow for immediate-continuous decision support within the user's currently investigated context without information inconsistency and redundancy. Such enhanced user experience is achieved by seamlessly augmenting the user's focal objects with the assembly of semantically relevant IoT data and the corresponding suggestions generated from the semantic data-object associations. A prototype interface has been implemented using a Microsoft Hololens AR display, however, due to COVID-19 social distancing requirements and prohibitive costs associated with the commissioning of a fully equipped smart home, a VR smart environment was adopted as the testbed. This approach led to the creation of a remote user study which enabled a cross-comparison between the *STARE* and the typical in-situ smart home data-oriented decision support interfaces. The results emanating from this work serve to answer some key research questions:

- When compared to the typical in-situ smart home data visualization metaphor that provided data-oriented decision support, *STARE* has been shown to significantly lessen the information overload problem and significantly enhance system effectiveness for decision-making tasks in smart environments.
- While applying the *STARE*, the usage of the *focus + voice command* focus augmentation significantly mitigated the information overload issue; however, it did not bring significant improvement overall for system effectiveness.
- *STARE* failed to achieve scientifically significant improvement in user satisfaction.

Lessons learned from this novel remote MR simulation experiment also form an important contribution offering a novel alternative to in-person research studies.

Future work in this area needs to be conducted to replicate these results with a larger participant cohort, together with a comparison study in a physical smart environment. The provision of suggestions and relevant IoT data for explanation can be independently evaluated in the future to compare which of them contributed more to the enhanced decision support brought by *STARE*. Further enhancements to *STARE* incorporating machine learning will enable the automatic construction of semantic data-object associations. This enhancement will ensure *STARE* extensibility allowing for the creation of smart environments that deliver *truly* intuitive interfaces for a future empowered ubiquitous IoT world.

APPENDIX
POST TASK QUESTIONNAIRE A

See Table 3.

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