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Research article

Current state of the art and future directions: Augmented reality data visualization to support decision-making

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A R T I C L E I N F O

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A B S T R A C T

Augmented Reality (AR), as a novel data visualization tool, is advantageous in revealing spatial data patterns and data-context associations. Accordingly, recent research has identified AR data visualization as a promising approach to increasing decision-making efficiency and effectiveness. As a result, AR has been applied in various decision support systems to enhance knowledge conveying and comprehension, in which the different data-reality associations have been constructed to aid decision-making.

However, how these AR visualization strategies can enhance different decision support datasets has not been reviewed thoroughly. Especially given the rise of big data in the modern world, this support is critical to decision-making in the coming years. Using AR to embed the decision support data and explanation data into the end user's physical surroundings and focal contexts avoids isolating the human decision-maker from the relevant data. Integrating the decision-maker's contexts and the DSS support in AR is a difficult challenge. This paper outlines the current state of the art through a literature review in allowing AR data visualization to support decision-making.

To facilitate the publication classification and analysis, the paper proposes one taxonomy to classify different AR data visualization based on the semantic associations between the AR data and physical context. Based on this taxonomy and a decision support system taxonomy, 37 publications have been classified and analyzed from multiple aspects. One of the contributions of this literature review is a resulting AR visualization taxonomy that can be applied to decision support systems. Along with this novel tool, the paper discusses the current state of the art in this field and indicates possible future challenges and directions that AR data visualization will bring to support decision-making.

1. Introduction

Decision support system (DSS), commonly defined as the computer-based system used for assisting decision making (Finlay, 1994), has revolutionized decision making. With the advent of big data, DSS systems have been at the heart of many industries from the service industry, to politics, in mining to finance and even military decisions. In general their use, bar occasion much publicized mistakes, have led to improved decision efficiency and accuracy under numerous scenarios. As an important area of the information systems (IS) discipline (Arnott and Pervan, 2005), DSS mainly relies on data analysis and visualization to aid in decision-makers actions. However, under nowadays rapid growth in the data volume and generation speed, decision-makers could easily feel overloaded while simultaneously feeling the lack of related information for decisions at hand (Zhu and Chen, 2008). Accordingly in the age of Big Data, DSS designers have been exploring how to appropriately filter useful information from copious datasets and visualize the decision-support results intuitively to be well perceived with reduced cognitive load.

Augmented Reality (AR) was given the interpretation of "increased perception of reality" (Mekni and Lemieux, 2014) which is achieved by the provision of real-time interactions with the coexisting real and virtual. Accordingly, AR techniques have been widely applied for data visualization, showing several common advantages including hands-free interactions, instant data superimposition, spatially mapped AR data for bi-augmentations between physical and virtual spaces (Lee et al., 2008), context-aware data visualization in relevant location or situated visualized in relevant time. By constructing semantic and spatial associations between physical context and AR data (*data-reality relationships*), and allowing for intuitive tangible interaction and actionable insights for the relevant data (Olshannikova et al.,

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2015), AR data visualization tools reduce decision-maker's mentally effort, decision time, and required domain knowledge (Guarese et al., 2020b).

However, despite the increasing interest in applying AR data visualization for decision support, very few literature reviews have provided a deep dive into this area with clear future guidelines. Therefore, we conducted this literature review to explore how AR data visualization has been applied for decision support. Moreover, to explore how different *data-reality relationships* between the AR datasets and the decision-making contexts have affected the decision accuracy and efficiency, a novel taxonomy is proposed to classify the common AR data visualization strategies according to the semantic *data-reality relationships* involved in these approaches. Based on this AR data visualization taxonomy and Alter's DSS taxonomy (Alter, 1977), the collected literature was classified into multiple types of AR-based DSS and are then analyzed from multiple aspects, including their AR data visualization approaches, DSS categories, AR input to DSS, AR decision support data localization approaches, application areas, and overall development tendencies. By comparing these metrics of different AR-based DSS categories, deep insights can be gleaned from this literature review to show how different AR data visualization strategies have been applied to confront different decision-making challenges in various areas. According to the key findings from this analysis, specific research gaps become clear, and thus current challenges can be identified to indicate the future directions for this field. Therefore, this paper has made the following contributions:

- proposing an AR data visualization taxonomy based on the semantic *data-reality relationships*.
- connecting the proposed AR data visualization taxonomy and Alter's decision support system taxonomy to analyze 59 AR-based decision support systems collected from published literature.
- identifying the current challenges and future research directions based on the literature analysis.

This paper firstly introduces the background and methodology of this literature review in Section 2. Then proposes a novel AR data visualization taxonomy in Section 3 as the basis of the literature analysis. Next, Section 4 classifies the collected literature based on this AR data visualization taxonomy and one DSS taxonomy with a general discussion for each type of AR-based DSS. Section 5 analyzes the development of each type of AR-based DSS and teases out several key findings from multiple aspects. According to the key findings from the collected literature, Section 6 makes an overall discussion and suggests the future challenges. Finally, Section 7 draws the conclusion.

2. Background and methodology

This section first introduces the literature review background to illustrate the motivation and importance of this literature review. Next, it describes the methodology used to conduct this literature review, in which Alter's DSS taxonomy (Alter, 1977) and a newly proposed AR taxonomy are introduced as the basis of the methodology used within this literature review.

2.1. Why apply AR data visualization for decision support?

Zhu and Chen indicated that the decision-making process could be indirectly supported by technologies that facilitate the "grasp of domain knowledge" and enhance the "awareness of situations" (Zhu and Chen, 2008). The availability of information could lead to better decision-making outcomes by reducing the uncertainty involved (Varian, 2014), and visual representation of information is regarded as an important approach to enhancing a decision maker's ability to process the available information (Coury and Boulette, 1992).

Compared to traditional desktop-based data visualization, Augmented Reality (AR) data visualization has been shown to have advantages for time-sensitive and ubiquitous information needs. Thus AR visualizations have been proposed to facilitate decision-making effectiveness and efficiency by providing users with relevant contextual information to endorse their choices (Marques et al., 2019b). Mekni and Lemieux (2014) pointed out that AR presents a compelling user interface in context-aware computing environments by allowing people to perceive virtual information as existing in their surroundings (Chang et al., 2013).

Similarly, several novel AR data visualization techniques, such as Situated Visualization (SV) (Walsh and Thomas, 2011; White and Feiner, 2009b), Situated Analytics (SA) (ElSayed et al., 2016), and Embedded Visualization (Willett et al., 2017), have been explored to enhance the user's perception of the information by providing "clearer information presentation by directly associating the information with the relevant physical objects, more natural interaction for information exploration by touching and manipulating physical objects, and more sophisticated information analysis providing contextual and overall information". ElSayed et al. (2016). By constructing these semantic and spatial data-reality relationships, AR data visualization systems can efficiently filter relevant information and map the data representations with the user's current context and requirements. Accordingly, the ability of AR visualization to associate data with its physical context is one of the commonly agreed areas where AR has strong potential for use in the context of decision support.

A successful Decision Support System (DSS) not only needs to automate decision making, but more importantly, it needs to adapt to different-level decision-makers and semi-controlled problems (Martins et al., 2021). To successfully apply fixed datasets and limited online resources into semi-controlled and even dynamically-evolving decision contexts, a DSS needs to be context-aware enough to accommodate a decision maker's requirements at any given time. In this procedure, identifying the missed and highlighted part of the current decision context may be critical in selecting and filtering valuable data from the datasets. However, this capability of being aware of the current decision contexts is fairly limited in traditional visualization terminals, including big screen displays and portable tablets. For these traditional visualization terminals, the main data input strategies are limited to touch-screen interactions and voice inputs, which prompted the user to proactively expressed their current decision questions and information needs with UI interactions and voice commands. These interaction approaches distract the user from the external world where the decision questions actually happen to get necessary run-time input for further decision support, which therefore can fall short in decision scenarios where the user needs to pay attention to the real-world situation observations and reactions. Tablet cameras are also utilized to capture more contextual information about the external world to recognize the user's face IDs, to diagnose the patient's affected area (Miller, 1994), to predict the plant's current growth stages (Olaniyan et al., 2018), and so on. However, these DSS require the user to keep holding the tablet with its camera facing the targeted objects, which may distract the user from their current task at hand to keep checking and adjusting the camera view. This problem can be well solved by nowadays AR headsets thanks to the built-in webcam and microphones which work as user's extra eyes and ears that always keep monitoring the user's current visual field and surrounding sound following their head movements. Moreover, modern AR headsets such as Microsoft

HoloLens and Apple Vision Pro support user gaze detection that allows the system to accurately track the user's currently focused objects, allowing the DSS to accurately understand the user's current surroundings and the decision questions that they are confronted with. Therefore, compared to traditional visualization terminals, AR tablets and AR headsets can input more abundant and accurate contextual data to the DSS, allowing the DSS to provide more relevant and valuable information with less and even no reliance on the user's manual input.

On top of the limitations of contextual information input sources, traditional DSS systems usually isolate the decision support data visualization from the relevant decision environment and users. For those decision-making scenarios where the formal decisions are made within the offices or labs, desktop-based visualization of the decision support data can satisfy the user requirements. However, for most non-expert decision-makers, visualizing sophisticated and complex visual encoding on the desktops may not help them efficiently make their daily decisions. In these decision scenarios, compared to spending long time researching the sophisticated data analysis reports, having the most immediate and in-situ access to simplified data representations may be more helpful for the non-expert users to make instant decisions. Therefore, AR techniques may enhance the daily instant decision-making experience by visualizing the decision support data at the exact place where it is related to. The most typical AR navigation may be a perfect demonstration. AR navigation applications can localize an AR left arrow sign on the exact road corners where a left turn is required. Compared to the traditional navigation applications, the former visualization strategy allows the user to immediately notice the place where the given information indicates, instead of manually matching the map and the physical surroundings with multiple times of focus switching.

In summary, AR techniques can bring the DSS more abundant, accurate, and implicit contextual data inputs, and also allows the system to visualize the decision support data with more explicit associations with the physical world. Therefore, according to this contextual understanding and its association with the decision support data, the system designer should determine the optimal data visualization approach for the DSS to reveal the hidden pattern of the data and its practical meaning for the current context and the decision makers. Accordingly, when AR is applied to facilitate this procedure, the data-reality associations should be an important factor that affects the AR/DSS interface design.

2.2. Literature review methodology

This literature review is conducted through 5 phases: define, search, select, analyze, present. Google Scholar was used as the database to search conference papers, journals, and workshop proceedings articles from 2000 to January 2022. The keywords "Augmented Reality AND (decision-support OR decision OR decision-making)" were defined to search and filter relevant publications. Only English language publications that have proposed or demonstrated AR-based decision support systems or frameworks were selected from all returned results as relevant examples for analysis. In contrast, other publications that only mentioned relevant theories or future potential were excluded from the survey. Since AR-based DSS area has only attracted significant attention in recent years and is still in its early exploratory phase, this literature selection strategy yielded only 37 relevant publications.

The literature was analyzed according to the decision support data type and the AR data visualization approaches, in which the AR data visualization approaches are classified based on the semantic data-reality relationships. To facilitate the classification of the AR data visualization approaches, this paper proposes a novel AR data visualization taxonomy based on the semantic data-reality relationships. For classifying DSSs, a classic decision support system taxonomy is applied. Accordingly, these two taxonomies form two dimensions that allow this literature review to classify and analyze the collected literature and investigate how different AR data visualization strategies have been applied to different DSSs.

To simplify the presentation of the literature analysis, all papers that present multiple DSS or AR data visualization strategies are separated into multiple samples for analysis. Each sample only falls into one DSS category and one AR data visualization category. Therefore, 59 AR-based decision support system samples have been found, and each of them can be placed to a certain point on the 2D surface formed by the two taxonomy dimensions. To provide system designers with clear guidelines for selecting a suitable AR data visualization strategy for a given decision support dataset and a decision context, this literature review needs to answer several key focused questions in the AR/DSS design and development process: What is the decision context? How can the front-end interact with the decision support component? What is the location relationship between the user, data, and decision context? Accordingly, this literature review classifies and analyses classified samples according to the following aspects:

- AR data visualization categories involved by the samples: Each type of AR data visualization strategy shows different advantages for decision support, which has led to the variant development of these AR data visualization strategies in the decision support realm.
- DSS categories involved by the samples: By investigating the time tendency of the collected samples according to their DSS categories, it is possible to gain an insight into how each type of DSS has applied AR data visualization strategies to enhance decision support over the last twenty years.
- AR inputs to the decision support component: AR can enhance DSS by visualizing certain datasets and providing AR input to the decision support component. The proposed AR data visualization taxonomy has shown how different types AR data visualization strategies have been applied for various datasets. Therefore, the AR input of collected samples is also categorized, based on which this paper analyzes how each type of AR input has been utilized to enhance different categories of DSS.
- AR data localization approaches: Unlike traditional desktop-based DSS which isolates the decision support data from the physical contexts, the localization of AR decision support data directly affects how the user associates these data with the physical decision-making contexts. The localization approaches are determined by the semantic data-reality associations and, more importantly, the DSS categories. Analyzing the AR data localization approaches applied by the collected samples makes it clear how each AR data localization approach can benefit certain types of AR-based DSS.
- AR Data Input and Localization Approaches for Decision Support: In most AR-based decision support systems, AR input categories could directly affect what extra information the decision engine could abstract from reality, and the AR data localization approaches could affect how the output data can be associated with reality. Therefore, analyzing how AR data input and localization approaches are combined to enhance different decision support systems may reveal deeper insights of how AR techniques facilitate decision support from data retrieval to presentation.

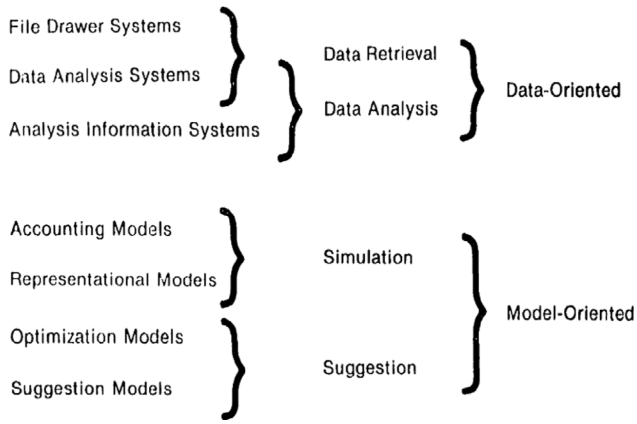

Fig. 1. Alter's decision support system taxonomy (Alter, 1977).

- Application areas involved by the samples: To investigate the development of different types of AR-based decision support systems in different application areas, this paper analyzes the distribution and development tendency of the common application areas involved by all collected samples.

The two primary dimensions in which each system will be classified relate to the chosen decision support taxonomy and the chosen AR visualization taxonomy respectively. These are introduced in the following sections.

2.2.1. Dimension one: Decision support taxonomies

Alter (1977) proposed the first classical DSS taxonomy to classify DSSs based on the system outputs, after which multiple new taxonomies were proposed (Arnott and Pervan, 2005; Pearson and Shim, 1994; Bohanec, 2003; Power and Sharda, 2007; Zhengmeng and Haoxiang, 2011). The leaf nodes (sub-categories without further sub-classifications) of most DSS taxonomies overlap, making the sample classification more complex and ambiguous. In contrast, in Alter's taxonomy all 7 DSS leaf node categories are extended along a single dimension without overlapping, making it possible to classify the samples into distinct categories. Moreover, compared to most DSS taxonomies that classified DSS based on hybrid metrics including decision support techniques and targeted end users (e.g. Arnott and Pervan, 2005; Zhengmeng and Haoxiang, 2011), Alter's taxonomy classified DSSs based on the results (decision support data types and generic operations) they presented to the end-users. Given the focus on AR data visualization and interaction approaches, this is a compelling advantage over competing DSS taxonomies. Thus, Alter's DSS taxonomy is utilized as one dimension to classify the collected AR-based DSS samples.

Alter et al. classified the DSSs into 7 distinct categories, which can be grouped according to similar characteristics, as is shown in Fig. 1:

- file drawer systems: provide online access to particular data items.
- data analysis systems: systems that allow the analysts to manipulate data and produce analysis reports; or allow ordinary users to perform general analysis actions such as data retrieval, pictorial representation, and summarization.
- analysis information systems: provide management information through a series of databases and small models.
- accounting models: use definitional relationships and formulas to calculate the consequences of particular actions.
- representational models: similar to accounting models but use non-definitional or partially definitional relationships to estimate the consequences of actions and conditions.
- optimization models: study and mathematically describe situations as complicated puzzles to analyze how to attain a specific objective.
- suggestion models: generates suggested actions based on formulae or mathematical procedures such as decision rules, optimization methods, etc.

Among the 3 data-oriented DSS categories, the analysis features provided to the users increase from the File Drawer Systems to the Analysis Information Systems. System complexity and implementation difficulties increase from the top to the bottom of the list: File Drawer Systems only need to visualize data items as the information retrieval tools, while Suggestion Models need to propose decisions based on the current situation. As Fig. 1 shows, compared to the data-oriented decision support systems which mainly provide information retrieval and data analysis, the model-oriented systems afford higher-level decision supports such as simulation and suggestion.

2.2.2. Dimension two: AR data visualization taxonomy

Since the concept of "augmented reality" was proposed, this area has witnessed rapid development in hardware support and application diversity. Thus numerous taxonomies have been proposed to classify the AR applications and modalities according to various dimensions. Normand et al. (2012) divided existing AR taxonomies into 4 categories according to their taxonomy criteria: technique-centered, user-centered, information-centered, interaction-centered.

Technique-centered taxonomies mainly focus on the visual displays (Milgram et al., 1995; Lindeman and Noma, 2007) or the technical features of the AR systems (Braz and Pereira, 2008), which exert much less impact on the design of the decision support systems compared to the other types of taxonomy criteria.

According to the interaction-centered taxonomies, the interaction between reality and virtuality are classified based on the location relationships between the AR displays and the physical targets (the physical referents of the AR content) (Mackay, 1998). Individual Physical Referents therefore can be seen as real world physical objects that data is associated with. Alternatively, the interactions are also classified based on the AR system architectures (Dubois et al., 1999). Chen et al. (2019) classified AR techniques according to the levels of the virtuality is related to reality ("weak", "medium" and "strong"). However, they defined the virtual-real relationships according to how the AR data is presented and interacted in user end, which depends more on the system designs instead of the dataset itself. To make use of the greatest advantages of AR data visualization for decision support, the data interaction and presentation strategies should be designed according to how the dataset intrinsically affect the physical decision environment and decision-maker users. In this way, how will the users interact and utilize the presented data are also mostly depends on such intrinsic data-reality relationships.

Information-centered taxonomies classified the AR systems based on the AR data dimensionalities (Suomela and Lehikoinen, 2004) and the presentation spaces (Tönnis and Plecher, 2011). These taxonomies focused more on the virtuality-reality interactions and information presentation strategies, which are important to the AR systems. However, most DSS taxonomies classify the DSS mainly based on the content provided to the decision-makers instead of where and how this content is present. Because these taxonomies tend to ignore the content of the displayed data and how the data may change user's perception of the physical contexts, they are less useful in the context of AR visualization within DSSs.

A few user-centered taxonomies show some consideration for the presented contents. Hugues and Fuchs (2011) classified AR systems into 5 sub-functionalities according to the association

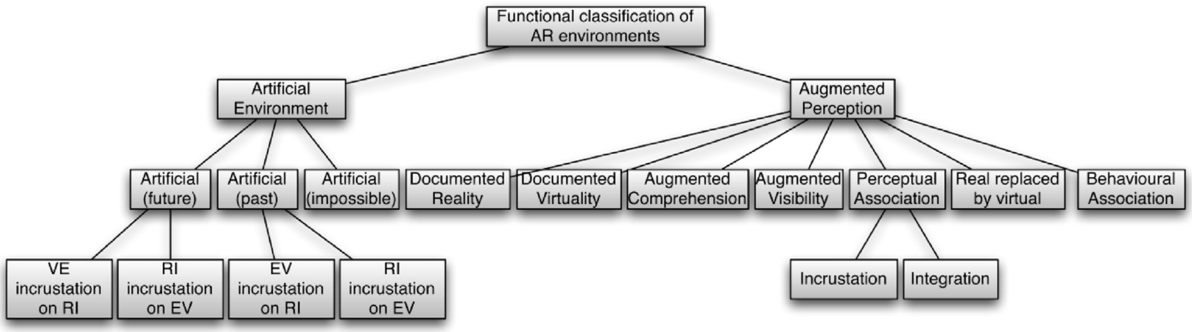

Fig. 2. Hugues's functional AR taxonomy (Hugues and Fuchs, 2011).

between the AR data and the reality (Fig. 2). According to this taxonomy, the AR contents are associated with reality either by creating an artificial part of the reality or providing augmented perception of the reality, in which the former category visualized the part of originally invisible reality while the latter category provided the information to allow for a better understanding of reality. This taxonomy shows more direct relevance with the AR-based decision support systems. However, the leaf nodes of this taxonomy tree (Fig. 2) classified the sub-functionalities according to mixed criteria of how the virtuality changes the perceived reality and how the virtuality is placed around the reality. This discontinuity in classification criteria makes it hard to distinguish different semantic associations between the AR data and the physical context.

As is mentioned above, the data presentation and interaction approaches of most AR DSS should be determined by the semantic and intrinsic associations between the decision support data and the decision contexts. Classifying AR data visualization strategies based on the semantic data-reality associations may allow DSS designers to quickly decide which type of AR data visualization can be applied and how it can facilitate the presentation and interaction of the decision support data in specific decision contexts. Such AR data visualization taxonomies would also allow for a clear classification and analysis of existing AR-based DSS. However, no existing taxonomy has clearly classified AR data visualization systems based on these criteria. Therefore, a new taxonomy is proposed based on Hugues' taxonomy (Hugues and Fuchs, 2011) (Fig. 2), to focus on the semantic data-reality relationships for AR data visualization classification. The following section explains the proposed taxonomy in detail.

3. AR data visualization taxonomy based on semantic data-reality relationship

The proposed taxonomy is presented as a tree in Fig. 3, in which each node represents a particular type of data-reality relationship. For better readability, this paper assigns abbreviations for 5 main branches of the taxonomy tree, which are important branches that will be frequently mentioned in the remainder of the paper. The following subsections describe each category in turn.

3.1. No intrinsic relationship between the AR data and the reality (NoRela)

Although there is still some debate as to whether superimposing digital data that shows no intrinsic relationships to the physical context can be regarded as Augmented Reality, several examples of this type of visualization strategy have been developed nevertheless. Thus it is included as a category in the proposed taxonomy (Fig. 3). For this type of data visualization strategy, there is no intrinsic semantic relationship (*NoRela*) between the superimposed data and the physical context. For example, the AR datasets do not update as the user's current situation changes nor do they integrate into the physical environment to form an integrated-logical context. Different from how Chen et al. (2019) described the AR data visualization approaches that showed "weak" virtuality-reality relationships, this *NoRela* category emphasized on the intrisic-semantic relationships between the dataset and reality which cannot be altered by the interaction and presentation designs. Such datasets can also be embedded into the physical environments and supports basic user interactions, but the changes in reality will not affect the dataset itself, which indicates no contexts exchange between the datasets and the external world due to the lack of intrinsic data-reality relationships. However, visualizing this type of dataset with AR displays provides certain advantages over traditional visualization techniques:

- **3D Visualization & Tangible Interaction Space**: for datasets with high dimensionalities and complex inner structures, AR visualization strategies allow the users to observe and manipulate the detailed data structure with intuitive six Degrees-Of-Freedom (DOF) interactions in a larger 3D space, which is not possible when using traditional screen-based visualization (e.g., Meiguins et al., 2006; Stasa et al., 2018; Wolle et al., 2018; Billinghurst and Duenser, 2012; Heller et al., 2019b).
- **Visible Collaborators**: this advantage is listed to draw a parallel with Virtual Reality (VR) visualization, which can also provide 3D visualizations and interaction spaces. In contrast to VR visualization, AR visualization strategies also allow the user to see local collaborators while working within a 3D data visualization and manipulation space. For collaborative data analysis tasks, direct communication with visible collaborators may improve task performance (Billinghurst et al., 1998b,a; Karlsson and Ng, 2017).
- **Scale Comparison**: Visualizing 3D models over the physical context in full scale gives the designers the original view of the designed model. Compared to the miniature model of designing using desktop-based visualization tools, designing the full-scale 3D model within a physical context allows the designers to detect scale inaccuracy in the early phases (Hockett and Ingleby, 2016).
- **Non-distraction Visualization & Interaction**: Simply superimposing digital data over physical context using AR Heads-Up Displays (HUDs) avoids distracting the user's attention from the task at hand (Henrysson and Ollila, 2004). Even without association with specific physical referents, this type of data visualization strategy significantly increases the convenience and safety for the visualization scenarios when the user is concentrating on other tasks, such as driving.

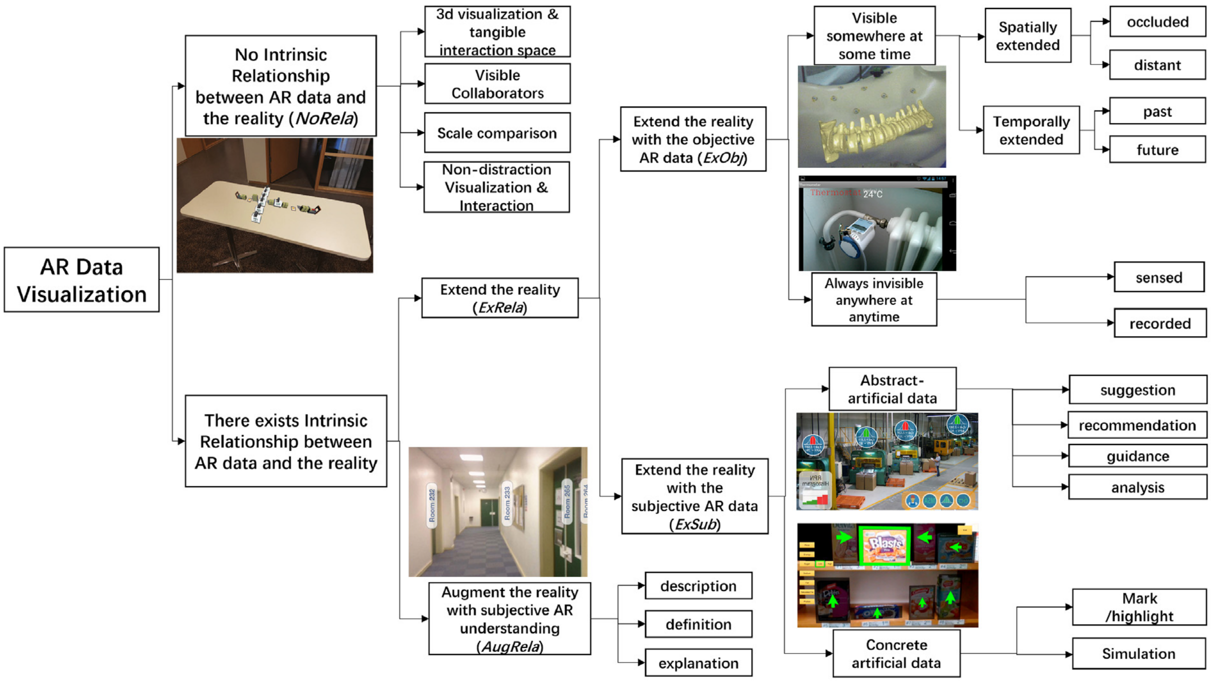

Fig. 3. AR data visualization taxonomy based on data-reality relationships: labels in parentheses are abbreviations for the category names used in the text.

3.2. There exists intrinsic relationship between AR data and the reality

All AR datasets that have an intrinsic semantic relationship with the physical contexts can play two roles within the physical context: Augment the reality with subjective understanding; or extend the reality with extra visibility or external knowledge. By playing the former role, AR information is associated with one or more relevant physical referents to augment the user's perception of them. This type of AR information is usually a subjective understanding of the associated physical referents, the data source of which is completely rooted in the physical context. By contrast, extending the reality means bringing extra visibility or external knowledge from outside of the associated physical context or referents.

A similar description of the AR extension role has been proposed as being important for decision support: "Augmented reality (AR) is a technology that can assist with our daily decision-making tasks by presenting information that extends the physical world" (Gutiérrez et al., 2019). This argument does not distinguish the AR extension from other types of AR visualization. Hugues and Fuchs (2011) divided AR systems into two semantic levels: reality with augmented understanding; and reality with augmented visibility. However, the latter level was limited to the imagery-augmented content. Moreover, as these two levels represent just one small part of their taxonomy, they are only briefly discussed here.

In our proposed taxonomy, all semantic relationships between the AR datasets and the physical context involve either the AR extending the reality, or augmenting the reality with subjective understanding. The taxonomy then contains several sub-categories under these two headings, which are described in detail below. In addition to the idea of augmented visibility proposed by Hugues et al. the extension to the reality in the taxonomy also refers to situations where external knowledge coming from new data sources are referenced as an addition to the associated physical referents. For example, superimposing other recommended products around a focal product (Zhu et al., 2004) should be regarded as an extension to the reality as these recommendations constitute new knowledge coming from data sources other than the focal products themselves. By contrast, superimposing a product description over a focal product is classified as falling into the category of augmentation to the reality with subjective AR understanding, since the product description is centered only around the focal product. Therefore, the main difference between these two roles is whether the AR data brings extra visibility to reality or if it references new knowledge from the external data source. The following sections will describe these two categories and their sub-categories in more detail.

3.2.1. Augment reality with subjective AR understanding (AugRela)

By augmenting the associated physical referents with AR understanding (*AugRela*), the AR data strengthens the user's perception about this physical referent with the superimposed data, which is normally subjective information centered around the associated physical referents. Good illustrations of it can be found from those AR annotations which superimposes some physical referents with the definitions (Al Delail et al., 2013; Platonov et al., 2006), descriptions (Reitmayr and Schmalstieg, 2004), and explanations (Santos et al., 2014) of them (Fig. 3). These AR datasets are all artificial information (text, images, and voices) used to strengthen the user's awareness and understanding of the associated physical referents, thus the AR data are normally located close to the physical referents to show the tight semantic associations as how embedded visualization (Willett et al., 2017) depicts. These datasets normally have simple structures as no extra visibility or new references are involved, thus they are widely applied in small-scale mobile AR applications for navigation, tour guide, and maintenance assistance. Similarly, Wither et al. (2009) divided AR annotations into 5 classes based on their semantic relevance to reality: names, describes, adds to, modifies, and directs to. The former two types of AR annotations fall into this category which augments the reality with AR understanding, while the other 3 classes add extra visibility or modifications to the reality.

3.2.2. Extend reality (ExRela)

AR extensions are not necessarily associated with specific physical referents. However, they are always associated with a specific context, which may convey some semantic information including the user's location, requirements, preferences, focal objects, historical actions, and environmental changes. By connecting such semantic information from the associated context and possibly integrating or analyzing it with new information outside of the context, this type of AR dataset introduces additional visibility or external complementary knowledge into the associated context to satisfy the user's visual or information requirements. This type of AR dataset is regarded as an "extension" to reality as it extends the original associated context with external contents (*ExRela*). As this AR extension is not necessarily centered around individual physical referents, it is sometimes not located close to any individual physical referent but instead appears as integrated situated information displayed over relevant physical context, as Situated Visualization has been depicted (White and Feiner, 2009a). For example, hovering a virtual path over a physical site to navigate the user (Zheng and Campbell, 2019) can be regarded as extending the physical site with extra visible routes. This virtual path is not centered around any specific physical referent but is associated with the user's current context in terms of location and requirements. Moreover, the AR extension can show diverse data-reality relationships: associating multiple physical components of the user's context to provide an integrated continuous analysis of the physical environment based on external information; introducing extra visibility as a logical part of the original context to form a new integrated context; or providing context-aware information that is relevant to the user's immediate requirements, inferred from their current context.

Both objective data and subjective/artificial data can be visualized as AR extensions, in which the former depicts or simulates the objects that exist in the physical world while the latter is formed by the subjective perspectives of human users. Differentiating whether the AR extension data is objective or subjective can help identify the AR data visualization system's purpose and potential application contexts. Therefore two sub-categories are proposed to distinguish the subjective extension and objective extension to reality (Fig. 3).

Extend Reality with Objective AR Data (*ExObj*) Some AR systems extend the physical context by depicting parts of reality that are invisible in the current context. For example, one sofa in an IKEA factory can be visualized in the customer's house with AR technologies to make it visible within the customer's physical context (Heller et al., 2019a). Here, the AR sofa is objective data as it is depicting a sofa that exists in the factory but is invisible to the customer due to the distance. By visualizing these existing objects which the user cannot perceive, extra visibility is added to the user's physical context. The following sub-categories are listed to describe different types of objective AR extensions to reality (***ExObj***).

- **Temporally Extended Reality**: AR is widely applied to visualize historical data that existed in the past reality and future data that is predicted to happen in the future reality. The depicted objects were or will form part of the reality at some time but may not exist in the user's current context. Visualizing these datasets allows the user to see an extended reality in terms of time by restoring past reality or depicting a predicted future reality. Typical examples of extending the current physical context with past reality can be found in the AR applications that in-situ superimpose the past appearances of historical sites, which allow for the immersive understanding of the history that happened at the associated sites (Cavallo et al., 2016; Pacheco et al., 2015). AR future planning systems are also widely applied to support architecture design and management by visualizing the 3D building designs at the construction sites (Schubert et al., 2015; Hockett and Ingleby, 2016; Golparvar-Fard et al., 2009). Visualizing these future data allows for earlier detection of flaws and easier on-site decision-making.
- **Spatially Extended Reality**: Users usually hope to see some objects existing in distant or occluded places, and AR can visualize these objective datasets that are initially invisible to the user due to spatial limitations. By visualizing these distant or occluded objects, these spatial limitations are overcome to provide users with extra visibility of the inaccessible places. For example, a patient's internal anatomy occluded by the skin could be in-situ superimposed over their body to assist the minimally invasive surgery (Bichlmeier et al., 2007).
- **Always Invisible Anywhere at Any Time**: On the opposite to the spatial and temporal extensions to reality, some objects existing in the real world are never visible to human eyes, such as the airflow, temperature, and moisture. The invisibility of these objective datasets and the common application of sensors and the Internet of Things (IoT) in diverse areas make the requirements to visualize sensor data increasingly significant in recent years. AR plays a vital role in making the visualization of these sensor data more in-situ and ubiquitous (Leppanen et al., 2014; Gushima and Nakajima, 2017; Park et al., 2016; Baskaran, 2018; Jo and Kim, 2016; Phupattanasilp and Tong, 2019; Alam et al., 2017). Apart from being collected by sensors, these invisible objective data can also be recorded from scientific analysis, such as soil chemical composition (Zheng and Campbell, 2019; Phupattanasilp and Tong, 2019; Xi, 2018). Therefore, these recorded scientific analyses and sensor data can be superimposed over the associated physical context.

Extend Reality with Subjective AR Data (*ExSub*) Subjective AR data is commonly visualized to extend the reality with extra artificial visibility and subjective perspectives. In contrast to the objective AR extension (***ExObj***), this type of dataset is formed by people's subjective willingness and artificial knowledge that are relevant to the user's physical context. This subjective AR data is not centered around individual referents but is formed with the information about multiple physical referents within the context and is alternatively built upon new knowledge outside of the context. The subjective AR extension can be concrete AR elements to add extra artificial visibility or abstract information to provide additional subjective knowledge:

- **Abstract Artificial Data**: Superimposing abstract artificial data over the relevant context introduces new knowledge, which normally works as supplementary information for the associated context. This supplementary information is normally provided based on the overall situation of the user's context, which can be perceived from multiple contextual parameters. For example, to provide step-by-step AR maintenance guidance for technicians, the relevant position information between multiple components of one machine as well as the user's historical maintenance steps both need to be considered (Marques et al., 2019a). In this example, the guidance extends the user's context with a subjective understanding of the maintenance task. Other good illustrations of the abstract artificial extension include visualizing the environmental analysis for the current context (Guarese et al., 2020b), recommending similar products for any selected product (Gutiérrez et al., 2019), and suggesting relevant resources based on a user's search history (Hahn, 2012). In this proposed taxonomy, the suggestions, recommendations, and guidance refer to different types of supplementary information: the "recommendation" indicates recommending alternatives that are similar to the items that have been selected, searched, or focused on by the user; "guidance" indicates instructions about how to complete a certain task that is defined by the user; "suggestions" indicate the possible solutions to the user's inquiries and issues, which are provided by the system according to the user's current situation, predefined decision rules, and criteria.

- **Concrete Artificial Data**: Superimposing concrete and artificial data over the relevant context introduces extra visibility according to the user's subjective imagination. These types of concrete-artificial data are not used to depict any reality but describe the modified reality according to the designers' or users' imagination. Such modified reality is typically constructed to facilitate understanding of the actual reality. For example, some AR surgery assistance allowed the user to highlight or mark the affected parts to show noticeable places, where these highlights help doctors to observe and diagnose the affected areas efficiently (Chen et al., 2019; Shenai et al., 2011) . Another example is the AR 3D models simulation, which has been used to visualize possible results under certain assumptions (Mao et al., 2017).

3.3. Discussion on the taxonomy

This taxonomy classified AR data visualization techniques into 4 main categories: *NoRela*, *AugRela*, *ExObj*, *ExSub*. In this order, the complexity of data-reality relationships and system design difficulties increase from *NoRela* to *ExSub*. As is mentioned above, in the *NoRela* category, the datasets have no intrinsic associations with reality and the changes in the physical world will not gain responses from the presented data. In the *AugRela* category, the datasets are generated based on certain physical referents for description, definition, and explanation, which bring the datasets strong relationships to reality. The location and type of relevant physical referents directly changes the content of the AR data that augments it. Therefore, in the *AugRela* category, the data-reality associations are commonly strong but in low dimension. By contrast, in the *ExObj* and *ExSub* categories, the AR data is not centered around any single physical referent but an entire physical environment, which means there may exist multi-dimensional data-reality associations. To infer what extra information is missed but required in a given physical environment, the designer need to analyze the targeted user scenarios and environments from multiple aspects, which may include the possible physical referents that may appear there, the tasks that the user may conduct there, the potential changes that can happen there, the new data input the system can obtain from the environment, and the interactions between the user and the environment, etc.. Based on such thorough analysis of the targeted environment, the designer may start to understand what essential information is missed there and decide what datasets can be embedded into the environment as a valuable extension to help the user's task completion. Such multi-dimensional data-reality association and integrated environment analysis lead to a higher complexity in dataset filtering and visualization design.

On top of such complexity of the AR extension visualization, the design complexity between the *ExObj* and *ExSub* categories also differ. Extending the physical environment with objective extension requires the system to visualize objective data that originally exist in the given environment but are somehow invisible to users. To obtain such extension datasets, the system designer is given a fairly restricted scope: the given local or remote usage environment with the supplementary information obtained from scientific measurement tools in extended timeline. However, to retrieving and filtering valuable datasets for *ExSub* categories, the data sources are not limited to above scope. Apart from the information that can be obtained from the given usage environment, any other subjective information should be obtained from multiple groups of relevant people, which may include certain domain experts, system stakeholders, end users, end user's collaborators, or even ordinary users in similar domains etc. Therefore, another tasks before searching the valuable subjective extension datasets is to define the people groups that can provide useful information for the targeted user scenarios and environment. After these people groups are defined, another challenging task making trade-off between potentially mutual-conflict input, evaluating the contributions and validity of the inputs from different groups and weighing these inputs accordingly. These tasks require substantial pre-analyzing work and fruitful experiences and domain knowledge of the system designers.

Therefore, in each AR data visualization category, the data searching, filtering, pre-analysis, and presentation steps all require understanding of the end users and usage environment to different extent. Categorizing AR data visualization strategies according to the data-reality relationships and analyzing the usages of these techniques from multi-dimensional aspects may give clearer instructions and inspirations to the system designers.

4. Sample distribution along two taxonomy dimensions

Having outlined our AR data visualization taxonomy and identified a suitable DSS taxonomy, this section analyzes the 59 AR-based decision support systems that described in 37 papers collected from the literature searching. In Table 1, all 37 papers are summarized and classified according to the involved AR data visualization categories and DSS categories. By categorizing them according to these two taxonomies, all the 59 samples are illustrated in Fig. 4: a scatter bubble chart in which each bubble stands for one type of AR-based decision support system. In each case, the X coordinate stands for a sample's AR data visualization category and the Y coordinate stands for its DSS category. The size of each bubble represents the number of samples that fall into the appropriate category.

The X coordinate of each analyzed system denotes the leaf of the AR data visualization taxonomy tree (Fig. 4) it falls into. As there are 16 leaves in this taxonomy tree, to aid the analysis, the 4 main types of AR datasets proposed in Section 3 are displayed along the X-axis: the AR data with no semantic data-reality relationship (*NoRela*), the subjective AR understanding used to augment reality (*AugRela*), the AR data used as the objective extension to reality (*ExObj*), and the AR data used as the subjective extension to reality (*ExSub*). In addition, to give a deeper insight into the distribution, several important sub-categories are also separated by dashed lines.

The 7 categories from Alter's DSS taxonomy are shown on the *Y*-axis, with the model-oriented and data-oriented DSS categories displayed separately.

Fig. 4 is thus divided into 8 zones (two DSS categories and 4 main AR categories). One zone (AugRela/Model Oriented) does not contain any samples. The following subsections discuss the 7 populated groups of AR-based decision support systems in turn.

4.1. AR data visualization with no semantic data-reality relationship (**NoRela**) applied for data-oriented DSS

As Fig. 4 shows, only one AR-based decision support system falls into this group, which enhances data-oriented decision support systems with AR data that shows no semantic association to the physical context. Heller et al. (2019b) developed

Table 1
Paper summary according to the AR data visualization taxonomy(Section 3) and Alter's DSS taxonomy (Alter, 1977).

AR data visualization categories	DSS categories	References
Augment the reality with AR descriptions; Extend the reality with the subjective AR data	Analysis information systems; Optimization models	Kaklauskas et al. (2015)
Augment the reality with AR descriptions; Extend the reality with the subjective AR data	File drawer systems	Zhu et al. (2004) and Irizarry et al. (2013)
Augment the reality with AR descriptions; Extend the reality with the subjective AR data	File drawer systems; Data analysis systems	ElSayed et al. (2016)
Extend the reality with the objective AR data	Analysis information systems	Alam et al. (2017) and Sangiorgio et al. (2021)
Extend the reality with the objective AR data	Data analysis systems	Guarese et al. (2020a), Schall et al. (2008) and Zulkifli and Md Nor (2021)
Extend the reality with the objective AR data	File drawer systems	Phupattanasilp and Tong (2019), Gomes et al. (2012) and Wake et al. (2018)
Extend the reality with the objective AR data	File drawer systems; Analysis information systems	Xi (2018)
Extend the reality with the objective AR data	File drawer systems; Suggestion models	Marques et al. (2019a)
Extend the reality with the objective AR data	Representational models	Olsson et al. (2012), Anagnostou and Vlamos (2011) and Wang et al. (2013)

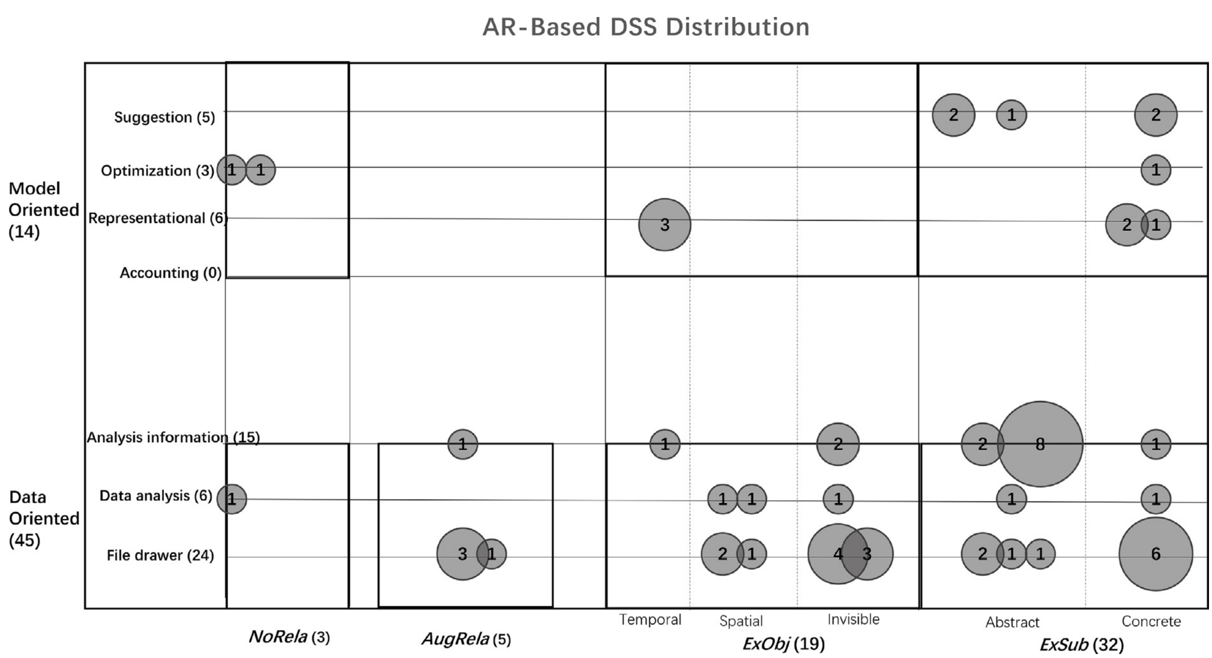

Fig. 4. AR-based DSS distribution: the X axis shows the AR data visualization categories (axis titles are abbreviations introduced in Fig. 3) according to the proposed AR data visualization taxonomy based on the data-reality relationships, and the Y axis shows the DSS category. The bubble label and size stands for the number of analyzed systems falls into this group of AR-based DSS represented by this bubble. The dash-line stands for the borders between sub-categories within the same AR data visualization category.

a multi-sensor AR application to allow for interaction with AR product holograms. Compared to traditional online retailing services, which required the customers to imagine the tangible experience of products, this strategy increased the customers' decision comfort as it allowed users to manipulate the AR product hologram with auditory feedback.

Unlike the IKEA furniture hologram visualization (Heller et al., 2019a) where the AR furniture was aligned with the floor and other physical furniture to form an integrated scene as in the imagination, the product holograms provided by this online retailing AR service are independent of the user's physical context or local physical referents. Therefore, this AR product visualization system showed no semantic data-reality relationship. However, the intuitive AR interactions and 3D visualization space did provide a more tangible online shopping experience for the customers to improve their decision comfort.

4.2. *AR data visualization with no semantic data-reality relationship (**NoRela**) applied for model-oriented DSS*

AR holograms were also applied to simulate manufacturing systems and provide available solutions to potential bottlenecks identified by the model (Karlsson and Ng, 2017). Stakeholders were allowed to observe the AR simulation models and discuss the provided solutions to make decisions on improving manufacturing systems (Karlsson and Ng, 2017). By identifying the possible bottlenecks and providing multiple available solutions based on the simulation, this system falls into the optimization model DSS category. These AR simulation models were designed to be placed on any surface and show no semantic relationships with the physical context, while the authors stressed the importance of the AR holograms for multiple viewing angles and the AR model scaling capabilities. Also, as a collaborative decision support system, using AR instead of VR to present a 3D simulation model allows for direct communication with visible local collaborators. Therefore, this system is treated as two samples which respectively show how AR data visualization can enhance optimization models by providing a 3D visualization space and by allowing for direct discussion on the optimization analysis among visible collaborators.

*4.3. Augmenting reality with subjective understanding (**AugRela**) to enhance data-oriented DSS*

As Fig. 4 shows, the AR data visualization systems that augment reality with subjective understanding have only been found to implement data-oriented decision support systems.

4 samples augmented specific physical referents with AR understandings, among which 3 visualized descriptions and one visualized definitions for the associated physical referents. Such AR data provided online access to particular data items relevant to the decision-involved physical referents; thus, they are all regarded as file drawer systems. Product descriptions, such as nutrition content and advertising information, were superimposed over the focal product to impulse decision making (Zhu et al., 2004; ElSayed et al., 2016). Similarly, augmenting facilities under maintenance with superimposed descriptions has been demonstrated to enhance the decision-making process of facility managers within a dynamic-complex working environment (Irizarry et al., 2013). The names of physical referents were overlaid over the power outlets, exits, and special seats of the classrooms as AR definitions to assist ordinary daily decision making such as choosing a seat (Guarese et al., 2020b).

In contrast to these data item augmentation systems, a different system that falls into the AugRela category overlaid detailed interactive property descriptions based on multiple weighted criteria to assist with property purchasing decisions (Kaklauskas et al., 2015). This falls into the DSS category of the analysis information system.

*4.4. Extend the reality with objective AR data (**ExObj**) to enhance data-oriented DSS*

16 samples fall into the category that extends the reality with objective AR data to enhance the data-oriented decision support systems (Fig. 4). Of these, 5 samples spatially extended the reality, and 10samples extended the reality with initially invisible objective data. One sample was found to enhance data-oriented DSS with AR temporal extensions.

By visualizing distant or occluded objects, multiple systems provided a spatially extended decision-making context for the users. To help drivers decide whether it is safe to engage in passing maneuvers, an AR driving assistant system overlaid a real-time video stream on the windshield to visualize the road ahead, which was occluded initially by the car in front (Gomes et al., 2012). Similarly, to support surgical planning and decision-making during robotic partial nephrectomy, occluded anatomy was visualized (Wake et al., 2018). The AR extension of distant reality was also applied to support remote surgical decisions by visualizing the remote operator's hand and instruments (Shenai et al., 2011). These 3 file drawer systems provide online access to particular distant or occluded objects to assist decision-making that requires information from invisible spaces.

Spatially extended AR data was also applied in data analysis systems. An urban planning DSS in-situ overlaid the subsurface infrastructure information on the ground to support virtual redlining (Schall et al., 2008). Alternatively, an AR virtual try-on application (Zulkifli and Md Nor, 2021) was designed to support outfit decisions by allowing for basic outfit searching and comparison actions.

The type of AR data that is always invisible includes recorded scientific analysis and sensor data. These have also commonly visualized to support decision-making tasks, for example those involved with environmental changes. Situated soil sensor data, recorded soil chemistry properties, and recorded crop analysis were visualized to support the precision farming decisions (Phupattanasilp and Tong, 2019; Xi, 2018; Zheng and Campbell, 2019). Similar file drawer systems have also been found to support general daily decisions with spatially visualized environmental data such as airflow and people circulation (Guarese et al., 2020b). In addition to these spatially visualized environmental data, general data interactions, including searching, filtering, and selection, are allowed for more complex decision-making contexts, such as electromagnetic compatibility (EMC) related tasks. The measured EMC field was visualized as 3D field topologies and 2D color-coded ray casts in a data analysis system to help users detect electromagnetic interference that may cause the equipment malfunction (Guarese et al., 2020a). To provide instantaneous analysis for quick decision supports involved in more complex smart environments where multiple heterogeneous sensor data are available, two analysis information systems filtered sensor data coming from different inputs with thresholding and fusion processes (Alam et al., 2017; Zheng et al., 2022a) before presenting the decision support data.

The only AR data-oriented DSS that visualized temporally extended data was found to be an analysis information system that supports multicriteria architectural decision-making (Sangiorgio et al., 2021). This system visualized the 3D models of a set of building materials and the multicriteria ranking analysis on the construction site where these materials are planned to be applied in the future, based on which even non-expert users may also easily find the most suitable building material from a set of alternatives.

According to these 16 samples that extend the reality with objective AR data, the distant or occluded AR data and the sensed or recorded scientific measurements are only found to be visualized for data-oriented DSS. Only one temporally extended AR data was visualized for data-oriented DSS.

*4.5. Extend the reality with objective AR data (**ExObj**) to enhance model-oriented DSS*

Only 3 model-oriented decision support samples were found to visualize objective AR data as an extension to the physical context, and all these 3 samples fell into the DSS category of representational models. All simulated the future reality to estimate the possible consequences of specific actions. To enrich the understanding of building plans and support construction decisions, an AR representational model (Olsson et al., 2012) in-situ overlaid the simulated 3D models of the planned architecture on the construction site, which was found to be advantageous compared to the traditional printout-based visualizations. Similar representational models are also commonly applied for architecture engineering decisions by presenting the "as-planned and as-built" progress or support efficient communication by allowing the project manager to obtain architecture information in different locations (Wang et al., 2013). In addition, such future data visualization was regarded as a promising strategy for urban planning decisions. It was reported that by in-situ visualizing the future planned constructions for residents, users were more intuitively involved in the decision-making process that affects their daily life (Anagnostou and Vlamos, 2011).

4.6. Extend the reality with subjective AR data (**ExSub**) to enhance data-oriented DSS

As Fig. 4 shows, most samples (23) fall into this category where a subjective AR extension was visualized to enhance data-oriented decision support systems, where 15 samples extended the reality with abstract-subjective AR data and 8 samples added extra visibility to the physical contexts with concrete-artificial AR data. AR marks and highlights were visualized as concrete subjective extensions to the reality in file drawer systems (Setiyawan, 2013; Eyraud et al., 2015; Irizarry et al., 2013; Shenai et al., 2011; Chen et al., 2019; Zheng and Campbell, 2019), data analysis systems (ElSayed et al., 2016), and analysis information systems (Zheng et al., 2022b) respectively.

Beginning with file drawer systems, AR marks and highlights are commonly applied for medical treatment and rehab decisions. By highlighting the identified critical anatomic structures (Shenai et al., 2011) and metastatic breast cancer in lymph nodes (Chen et al., 2019) with colored AR marks, the doctors are informed with continuous therapy decisions during the surgical training and coordination process. AR marks are also an important approach for superimposing guiding paths. One AR rehab system allowed the patients to wear AR headsets to complete rehab exercise following the highlighted path, during which the exercise progress data were recorded to assist the therapists' decisions on the treatment plan (Setiyawan, 2013). Such AR file drawer systems were also applied for driving assistance by highlighting the road signs to impact the driver's visual attention during the decision-making phase (Eyraud et al., 2015). When applied for maintenance work, the objects that can be used to support decisions were highlighted with AR outlines to assist the locating-the-right-object task (Irizarry et al., 2013). Such AR outlines have also been applied for precise farming to highlight the field zone boundaries and assist the farmers' decision-making on soil treatment (Zheng and Campbell, 2019).

With customized information retrieval and filtering actions, AR highlights were also applied to the more complex data analysis system by highlighting the products that satisfy the user-defined metrics with data filtering and retrieval operations (ElSayed et al., 2016).

AR marks were also applied in an analysis information system (Zheng et al., 2022b) to in-situ highlight the underperforming areas of crop fields with yield underperformance analysis, which navigated the users to the identified underperforming areas and allowed them to mark diagnosed issues with AR annotations.

From Fig. 4, it is obvious that abstract-subjective AR extensions are more commonly applied to data-oriented decision support systems than model-oriented systems. When applied within file drawer systems, users were provided with online access to superimposed product analysis (Jain et al., 2018), nutrient guides (Gutiérrez et al., 2019), and product recommendations (Zhu et al., 2004; Gutiérrez et al., 2019) to support their shopping decisions. Othman et al. (2021) designed a free-hand AR application to assist operators in finishing a chemotherapy drug preparation correctly. By recognizing and checking the drug samples and volumes with AR web cameras, and providing step-by-step guidance following the operator's voice command, this data analysis system ensured drug preparation safety using hands-free AR monitoring techniques.

More samples fell into the DSS category of analysis information system, which directly superimposes the analysis reports that combined multiple datasets and analysis metrics. One house purchasing decision support system was designed to in-situ overlay the recommendations of alternative properties with multiple weighted criteria comparisons (Kaklauskas et al., 2015). In a highly dynamic decision-making context, it is necessary to provide context-aware analysis reports by combining multiple real-time environmental measurements according to predefined rules and models. For example, by analyzing multiple measurements such as airflow, seat occupation history, WiFi signal, and power outlets, the analysis information system was able to spatially overlay seat comparison to help the user select suitable seats according to a set of user-defined criteria (Guarese et al., 2020b). Similarly, by combining multiple sensor data and predefined Key Performance Indicators (KPI) schemes, analysis information systems can in-situ display real-time reports about the KPI of each workstation inside an industrial plant to assist manufacturing management (Segovia et al., 2015).

Additionally, a COVID-19 cyberinfrastructure framework (Li and Zhang, 2021) was proposed to visualize real-time spatial analysis of how pandemics affect human emotion changes to support risk-informed decision-making by analyzing social media streams, confirmed cases, and crime rates. In a similar way, precise farming decisions may also be supported by in-situ spatially overlaying the soil and crop analysis such as crop decease prediction (Xi, 2018), and soil chemistry properties (Zheng and Campbell, 2019). When applied to military training, brief alerts of the contextual situation, such as "in attack range" and "in the radar area", were also overlaid to support decision making during an Unmanned Aerial Vehicles (UAV) mission (Wu et al., 2012). Analysis information systems that applied AR to support shopping decisions usually combine and filter product analysis, recommendations, and comparison based on user-defined criteria to assist the shopping decisions (Waltner et al., 2015; Gutiérrez et al., 2019).

4.7. Extend the reality with subjective AR data (**ExSub**) to enhance model-oriented DSS

9 model-oriented decision support systems were found to extend the physical context with subjective AR data (Fig. 4). When applied for representational models, AR simulation is a potential strategy to visualize the whole process of how specific actions cause possible consequences in the current situation. For example, It has been demonstrated that interacting with a simulated AR battlefield over the battlefield map is effective for military decision making by allowing for "perceived situation awareness" and "perceived usefulness" (Mao et al., 2017). AR simulation and AR highlights have also been applied in matching tasks to provide decision support for cognitively disabled, autistic, and trisomic children (Richard et al., 2007). When applied in the more complex optimization model, AR markers were applied to highlight the optimal choices from the physical context for the user based on the pre-defined goals. A good illustration is to compare the multiple products in front of the user and highlight the products that satisfy the user's requirements (ElSayed et al., 2016).

In a context that requires more information about the optimal actions to attain a specific objective, suggestion models were designed to display more complex AR markers with possible supplementary AR guidance or direct suggestions. The AR rehab assistant system allowed the therapist to suggest an AR path to guide the patient to move a specific object for rehab exercises (Setiyawan, 2013). Similarly, AR markers and AR guidance were also combined to support maintenance decisions by suggesting step-by-step actions for specific maintenance tasks (Marques et al., 2019a). A Mixed Reality collaborative learning system (Pan et al., 2021) superimposed each student's quiz result analysis over their head for the AR teacher client, based on which the system generated teaching suggestions to instantly support personalized teaching decisions for the teacher. Such direct brief suggestions were also superimposed onto home appliances and furniture to instantly support smart home decisions based on real-time relevant IoT data measurements (Zheng et al., 2022a).

4.8. Summary

According to Fig. 4, these 59 collected samples show several interesting characteristics in terms of the overall distribution. First, AR data visualization is more commonly applied to data-oriented DSS (45) than model-oriented DSS (14).

One possible reason might be the complexity differences between the data-oriented and model-oriented DSS on the system design and implementation. As is discussed in Section 2.2.1, model-oriented DSS involves the intelligent calculations and study of the decision-making context, thus requiring more complex databases and model designs. Compared to the development history of decision support systems, AR data visualization has started to gain research attention more recently, and its application for decision support aims has appeared even more recent still. This presumption can be supported by the observation that the highest number of AR-based DSS are file drawer systems (24): most samples applied AR to support decisions in the most straightforward manner. Another possible reason might be the common feature of AR visualization to blend the virtual data with reality, which shows obvious potential for decision support contexts that require situated visualization of on-site datasets or intuitive data manipulation.

Second, the type of AR data visualization that augments reality with subjective AR understanding was only applied for data-oriented DSS. In this AR data visualization category, all AR data is only centered around corresponding physical referents while no external information or extra visibility is involved. This data-reality relationship might have significantly limited the types of databases allowed for the decision support system, while model-oriented DSS typically requires the analysis and combination of multiple databases. More importantly, the models and algorithms required by model-oriented DSS are usually considered as external information for the decision-making context. Therefore, the restrictions on the resource of the AR understanding that is used to augment reality might have caused its limitations for more complex decision support contexts.

Third, among all 19 samples that extend the reality with objective AR data, only 3 samples (16%) fell into the category of model-oriented DSS. Except for the 3 representational models, which visualized future data to estimate the possible consequences of specific actions, no objective AR extension has been applied to the model-oriented DSS samples. To infer the reason behind this gap, the "objective" description of the AR data might have limited its application to the model-oriented DSS, which mainly outputs subjective estimations and suggestions to support the decision. Accounting models may provide objective outputs by calculating the consequences of particular actions based on objective contextual parameters such as sensor data, which might be a potential usage of the objective AR extension in model-oriented DSS. However, no accounting models were found to apply AR data visualization for decision support.

Finally, clusters (39 samples) are identified at the right bottom of Fig. 4 where AR extensions are applied to data-oriented DSS. Two reasons might cause this cluster: in the proposed AR data visualization taxonomy, the AR extension category covers the most sub-categories; also, extending the decision-making context with extra visibility or external knowledge means more data resources are allowed for the decision-makers, thus can be easily applied for data-oriented DSS.

5. AR-based DSS sample analysis

The sample distribution in the previous section has classified AR DSS into 7 groups according to the relevant AR data visualization strategies and DSS categories. While this classification gives a helpful overall view of system type distribution, it does not capture trends over time. Thus, this section first engages in a deeper analysis of the temporal trends in the development of this research area.

Section 2.2 outlines several other perspectives from which it is helpful to analyze the identified samples. Accordingly, after analyzing the temporal aspect, this section provides a higher-level analysis of the samples from the aspects of the AR input to DSS, AR data localization approaches, and application areas.

5.1. Development patterns of AR-based DSS over time

The line chart in Fig. 5 shows how the numbers of the above 7 types of AR-based DSS samples increase from 2004 to 2022, from which the development patterns of the AR-based DSS area can be seen over time. It is clear that among these, the most researched type is the data-oriented decision support system that extends reality with the subjective AR data (24 samples). This type of AR-based DSS has become increasingly popular since 2013. The number of data-oriented DSS samples that extend reality with objective AR data began increasing rapidly in 2017 and ranked in the top two by 2022 (16 samples). Since 2013, the two types of data-oriented DSS categories based on AR extensions have attracted much more attention than the other types of AR-based DSS, and this gap has grown since 2017. Among the other 5 AR-based DSS types, the model-oriented DSS that extends reality with subjective AR data (*ExSub*) is the only one that has kept increasing in research numbers from 2015 to 2022. The AR data without semantic relationship (*NoRela*) to reality has always been the least applied dataset for decision support systems.

Therefore, the subjective AR extension (*ExSub*) has been the most popular dataset applied in either model-oriented or data-oriented DSS since 2013. The objective AR extension (*ExObj*) has been showing significant research interest for data-oriented DSS since 2017. The other identified categories of AR-based DSS have not attracted significant attention in recent years.

5.2. Development patterns of DSS that apply AR data visualization

In Fig. 6, all 59 collected samples have been categorized into 6 groups according to their DSS categories per Alter's taxonomy (6 of the 7 DSS categories have been found to apply AR techniques for data visualization), and this line chart shows how the number of each group of DSS samples increases from 2004 to 2022. The file drawer system has always been the most common decision support system that applies AR techniques for data visualization. AR-based file drawer systems have become even more popular between 2017 and 2020. The analysis information system is the second most common DSS type among all collected samples, which proliferated from 2013 to 2015. Compared to these two types of data-oriented DSS, AR-based model-oriented decision support systems have been much less integrated with AR techniques. The representational model and optimization model samples have stopped increasing since 2017.

From these tendencies, it can be seen that the model-oriented systems have much less commonly applied AR data visualization strategies compared to the data-oriented decision support systems. Moreover, this gap between the data-oriented DSS samples and model-oriented DSS samples has been enlarging since 2017. However, between 2020 and 2022, this tendency has changed: the AR-based file drawer systems stopped increasing while AR-based suggestion models started gradually increasing. It will be interesting to observe whether this pattern continues into the future.

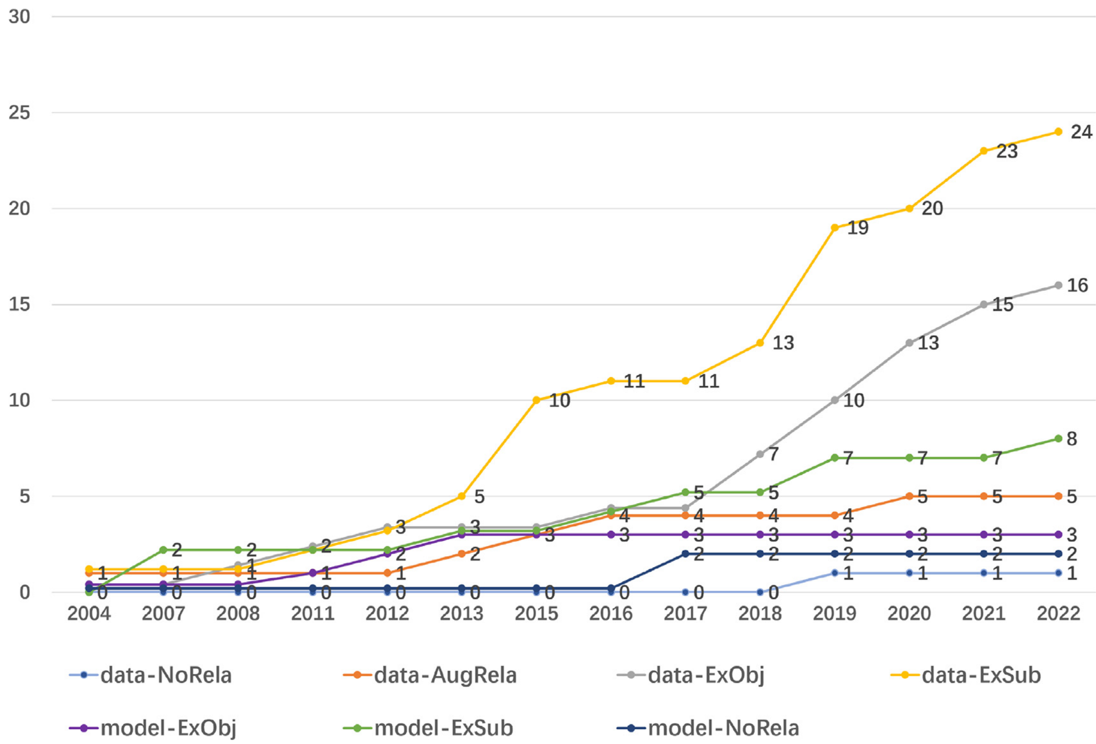

Fig. 5. AR-based DSS tendency: the X-axis shows the years, and the Y-axis shows the number of samples. Each line represents one AR-based DSS category.

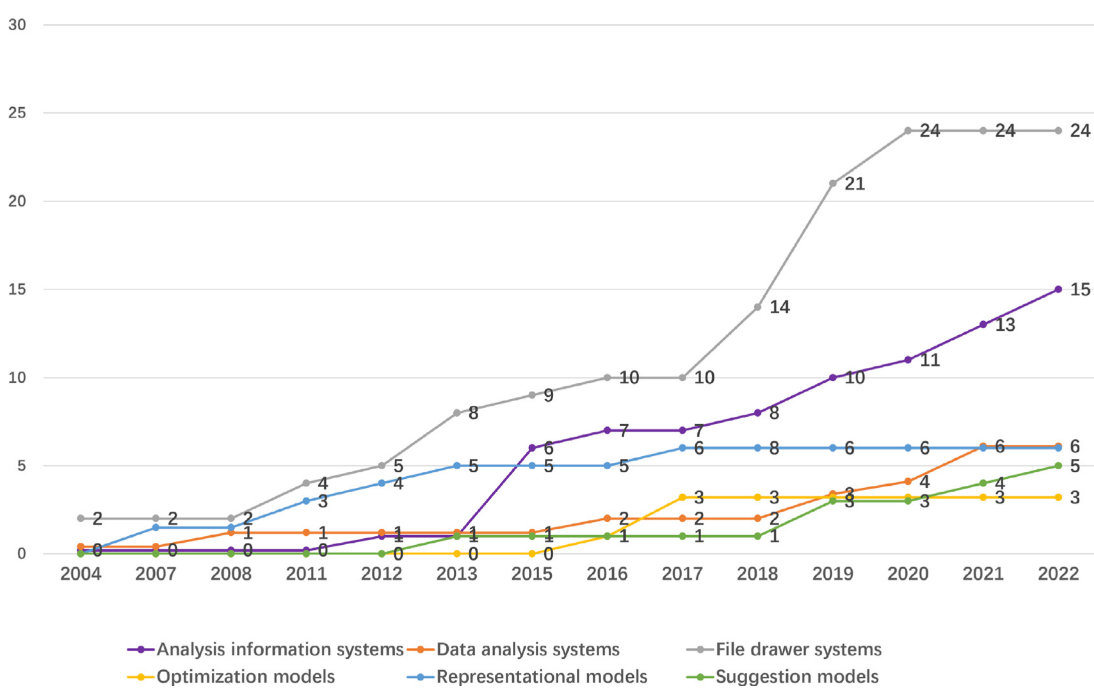

Fig. 6. Time tendency of 6 types of DSS categories among 59 collected samples: the X-axis shows the years, and the Y-axis shows the number of samples. Each line shows how the number of collected samples in one DSS category changes over time.

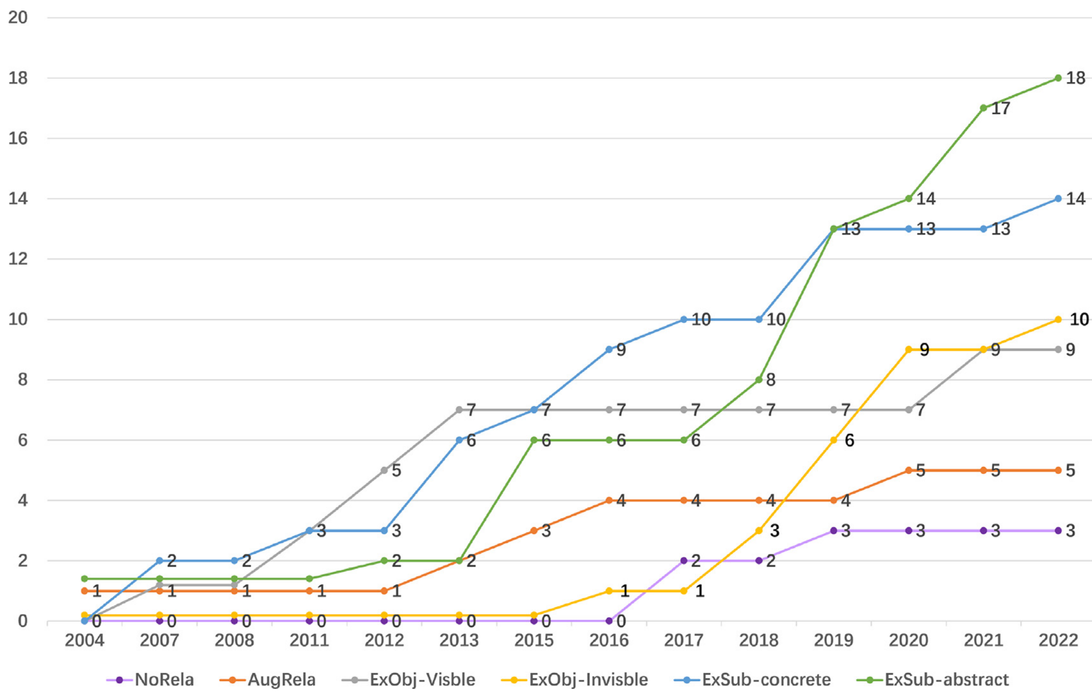

Fig. 7. The tendency of different AR data visualization strategies applied to decision support: the X-axis shows the years, and the Y-axis shows the number of samples; each line stands for one type of AR data visualization strategy according to the proposed taxonomy (legend labels are abbreviated).

5.3. Development patterns of AR data visualization in decision support realm

To clearly illustrate the tendency of how different AR data visualization strategies have been applied for decision support, Fig. 7 divides all collected samples into 6 categories according to the proposed AR data visualization taxonomy and visualizes the increase of each category over time. Based on the 4 main AR data visualization categories mentioned in Section 4, the subcategories of AR subjective and objective extensions are analyzed separately according to the proposed taxonomy (Fig. 3): the objective AR extension (*ExObj*) is divided into the extension of initially visible (*ExObj-Visible*) and invisible data (*ExObj-Invisible*), and the subjective AR extension is divided into concrete (*ExSub-concrete*) and abstract data (*ExSub-abstract*).

According to Fig. 7, the two types of subjective AR extension have always been the most applied AR data in decision support systems and have continued to increase rapidly in recent years. The number of DSS samples visualizing abstract-subjective AR extension (*ExSub-abstract*) started increasing rapidly since 2013 and slightly exceeded that of the concrete AR extension (*ExSub-concrete*) samples in 2019, which may indicate a tendency towards abstract-subjective AR extension for decision support in the future. The objective AR extensions have been less commonly applied for decision support than the subjective AR extensions. Interestingly, the two types of DSS samples based on the objective AR extensions showed opposite trends in terms of growth speed. The DSS samples that temporally or spatially extended the initially visible reality (*ExObj-Visible*) started increasing steadily from 2008 but stopped between 2013 and 2020. By contrast, the DSS samples that extended the reality with the initially invisible objective AR data (*ExObj-Invisible*), only appeared for the first time in 2015, accelerated from 2018 and had exceeded the former type of DSS samples by 2022. This difference between the growth trends of these two types of objective AR extension may have been affected by the popularization of the Internet of Things (IoT) and Wireless Sensor Networks (WSN). More daily decision-making tasks require the decision-makers to be aware of dynamic environmental changes, which peripheral sensors can directly provide in smart environments empowered by IoT or WSN. Therefore, in these contexts, the spatial visualization of these invisible environmental parameters may facilitate immediate and intuitive decision support.

Compared to the AR extensions, which introduce extra visibility or new external information to the current context, the subjective AR understanding of individual physical referents/real world physical objects that data is associated with (*AugRela*) and AR data that shows no semantic data-reality associations (*AugRela*) seem to allow for fewer decision-support possibilities than the AR extensions. The latter type of AR datasets has not been found in decision support research prior to 2017, which might also support the idea that the semantic data-reality associations provide significant advantages for on-site decision making. Overall, Fig. 7 shows the recent trend of visualizing subjective AR extensions and initially-invisible objective AR extensions to support decision making. The spatially and temporally extended AR data were commonly applied for decision support before 2013 but appear to have become popular thereafter. The other types of AR data have not attracted substantial attention in the decision support realm.

5.4. 5 Types of AR inputs to DSS

Augmented Reality not only features visual outputs that are blended with reality, but more importantly shows significant advantages for enabling intuitive interaction modalities through capturing visual or tracking inputs from the physical context. In most AR-based DSS, the decision support component takes inputs from the AR front-end, generates the decision support data based on these inputs, and returns it to the AR front end. These AR inputs vary, and tend to exert different effects for each type of decision support system. Therefore, to investigate how different types of AR inputs have been applied for decision support systems, 5 types of AR inputs are summarized from all the collected AR-based DSS samples. The collected DSS samples are found to utilize the following types of AR inputs to create, retrieve, and filter the decision support data:

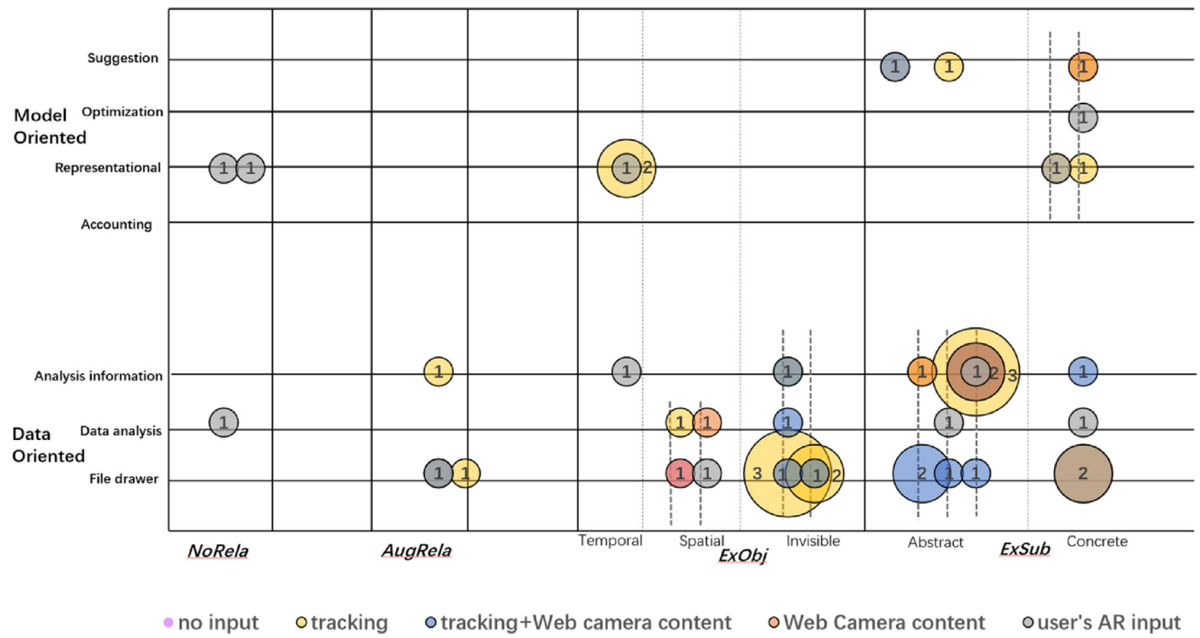

Fig. 8. Distribution of 5 types of AR input along the AR visualization taxonomy and DSS taxonomy: the *X* axis shows the AR data visualization categories (axis titles are abbreviations introduced in Fig. 3) according to the proposed AR data visualization taxonomy based on the data-reality relationships, and the *Y* axis shows the DSS category. The bubble label and size stands for the number of analyzed systems falling into each group. The bubble color stands for its AR input type. The dashed line indicates the borders between sub-categories within the same AR data visualization category.

- **No input:** very few AR-based DSS (1 sample) only applied an AR front-end to display decision support data but took no input from the AR front-end (Wake et al., 2018).
- **Tracking:** most AR-based decision support systems (22 samples) exploited AR tracking to filter and retrieve information from the decision-making contexts. These samples either retrieve data by tracking certain fiducial markers or take the user's current location and orientation data as the input to filter the neighborhood data (Kaklauskas et al., 2015; Alam et al., 2017; Guarese et al., 2020b; Segovia et al., 2015; Zheng and Campbell, 2019; Schall et al., 2008; Marques et al., 2019a; Irizarry et al., 2013; Richard et al., 2007; Olsson et al., 2012; Wang et al., 2013; Li and Zhang, 2021).
- **Web camera content:** 9 samples recognized the user's focal objects and context to create, retrieve, and filter relevant data to support the decision making (Wu et al., 2012; Waltner et al., 2015; Gomes et al., 2012; Eyraud et al., 2015; Chen et al., 2019; Jain et al., 2018; Zulkifli and Md Nor, 2021; Othman et al., 2021). This is usually achieved by analyzing the images captured by the web cameras on the AR display. This type of AR input allows for context-aware decision support as the system can construct the semantic associations between the decision maker's context and the decision support data to filter data according to what the user is viewing. Compared to the decision support system that take the user's location to filter information, recognizing the user's current focal context will be more adaptable for a highly dynamic environment.
- **Tracking + web camera content:** 12 samples combined AR tracking and web camera image recognition to create, retrieve, and filter decision support data (Gutiérrez et al., 2019; Xi, 2018; Phupattanasilp and Tong, 2019; Zhu et al., 2004; Pan et al., 2021; Zheng et al., 2022a).
- **AR data interaction:** 15 samples mainly rely on the user's interaction with AR data, such as 3D manipulation and gesture control, to generate the decision support contents (Guarese et al., 2020a; ElSayed et al., 2016; Heller et al., 2019b; Setiyawan, 2013; Shenai et al., 2011; Karlsson and Ng, 2017; Anagnostou and Vlamos, 2011; Mao et al., 2017; Sangiorgio et al., 2021; Zheng et al., 2022b). The AR input distinguishes itself from traditional data interactions for the 6 DOF gesture interactions and intuitive 3D AR model manipulation.

Based on these 5 types of AR inputs, their utilization in all types of AR-based DSS are illustrated in Fig. 8. Each bubble stands for a group of AR-based DSS samples (X, Y) that apply X type of AR visualization approach to the Y type of decision support system. The bubble color indicates the AR input it utilizes. The bubble size and labels indicate the number of samples falling into each group. As this figure shows, the AR input that solely relies on web camera content has only been found in data-oriented DSS, while the other AR inputs have been found in both model-oriented and data-oriented DSS.

From Fig. 8, it is clear that AR-based DSS samples most commonly utilize AR tracking as the input of the decision support component, which may be the easiest way to filter the decision support data that are spatially distributed. The second most commonly applied AR input to DSS is web camera content, which is usually applied to recognize the decision maker's physical context and sometimes combined with AR tracking to help refine the decision support data based on decision context and location. In other cases, the user's interactions with the AR data are the primary input to manipulate the decision support data.

Most samples fall into the category that takes AR tracking as the input to the data-oriented decision support component, which outnumbers the model-oriented decision support systems that take the AR tracking as the input. Based on the AR tracking input, file drawer systems and analysis information systems are allowed to provide access to data items (Guarese et al., 2020b; Irizarry et al., 2013; Zheng and Campbell, 2019) and analysis reports (Kaklauskas et al., 2015; Alam et al., 2017; Guarese et al., 2020b; Segovia et al., 2015; Zheng and Campbell, 2019; Li and Zhang, 2021) about the user's local surroundings. When applied to representational models and suggestion models, AR tracking usually utilizes marker trackers to locate specific physical referents and superimpose the pre-defined decision-support data bound to them (Richard et al., 2007; Marques et al., 2019a).

As Fig. 8 shows, the AR inputs that solely utilized web camera content have mostly been applied to visualize data-oriented DSS as an extension to reality. Utilizing web camera content to understand the user's current semantic context has been an important strategy to visualize the most relevant information. As is mentioned in Section 3.2.2, the AR data that extending reality is not necessarily tightly centered around specific physical referents but still relevant with the visualized environment, in which the data-reality associations are more opaque and indirect. Therefore, with a thorough understanding of the surrounding environments through visual input from web cameras, the AR system may construct an integrated association between all the recognized physical referents to conjecture what their combination means for the current decision contexts. Such integrated environment understanding may help the DSS decide what external knowledge is most demanded to extend the current decision contexts, which may automate the data filtering and mapping process for data-oriented DSS. Therefore, unlike manual user interaction, the webcam visual input allows the DSS to provide data-oriented extension in a more unobtrusive and automatic manner. Given that most nowadays AR glasses are equipped with at least one webcam which works as the system's "windows to the user's world", the AR web camera is one important input that helps the DSS understand the user's current situation and decision questions. This type of AR input is therefore widely applied in HUD AR DSS (Gomes et al., 2012; Eyraud et al., 2015; Setiyawan, 2013; Othman et al., 2021) and DSS targeted for non-expert users (Pan et al., 2021; Zheng et al., 2022a; Gutiérrez et al., 2019).

When applied for analysis information systems, web camera content is commonly applied to recognize the decision maker's physical context and focal objects (Wu et al., 2012; Waltner et al., 2015), and then provide a series of datasets that are semantically relevant to the recognized objects and context. Apart from the typical usage of object classification (Waltner et al., 2015; Wu et al., 2012), web camera content has also provided more types of information for file drawer systems and data analysis systems, such as a real-time stream of the situation at distant or occluded places (Gomes et al., 2012), keywords scanning (Jain et al., 2018), cancer identification (Chen et al., 2019), drug volume estimation (Othman et al., 2021), and body measurements (Zulkifli and Md Nor, 2021). Additionally, more file drawer systems combined sensory AR tracking and web camera content recognition to mitigate the web camera recognition inaccuracy for the outdoor decision context (Gutiérrez et al., 2019; Xi, 2018; Phupattanasilp and Tong, 2019; Pan et al., 2021; Zheng et al., 2022a). Combining AR tracking and web camera content analysis also allows for context-aware AR suggestion models that visualize relevant suggestions according to the user's current semantic contexts (Zheng et al., 2022a; Pan et al., 2021).

User interaction with AR data has been applied as the primary AR input in every DSS and AR data visualization category, which shows the essential role of user's input no matter what data-reality relationship the system presents or what decision questions the system solves. In the *NoRela* AR data visualization systems, the only context that the DSS can obtain is the decision maker's interactions with the presented data. In such systems, the user interactions may include the user's current action and the information needs that they explicitly expressed to the system by UI interactions or command input. Thanks to such user contextual data, these AR data visualization system can still provide relevant decision support for the users even without sufficient understanding about the physical environment.

When applied to file drawer systems, the user's interaction with the AR data was either used to help filter the data items presented to the decision maker (Setiyawan, 2013; ElSayed et al., 2016), or provide real-time visualizations for the remote clients in collaborative decision-making tasks (Shenai et al., 2011). For data analysis systems and analysis information systems, the user's interaction with the AR data plays a more vital role to perform general analytical actions such as data retrieval, selection, filter, and manipulation (Guarese et al., 2020b; ElSayed et al., 2016; Heller et al., 2019b; Zheng et al., 2022b; Sangiorgio et al., 2021). When applied in the suggestion models and representational models, the decision-making data can be directly generated by the user's interactions with the AR datasets. For example, the user's manipulation of the AR building models was directly input to the representational model to generate the future urban plan simulation in one sample (Anagnostou and Vlamos, 2011). This example took user's AR interaction as the main input to the decision system and generated the future simulation as the temporal extension to the current contexts. Another example (Setiyawan, 2013) tracked patients' rehab behaviors by analyzing the glove interactions in an AR suite, by inputting which the system predicted the patients future rehab progress to help doctors adjust further rehab planning accordingly. In this example, the predicted future rehab plan was directly visualized as AR marks to extend the patient's current view of surroundings, instructing their next step to improve their rehab exercises.

By investigating the distribution of 7 types of decision support systems along the Y-axis of Fig. 8, file drawer systems have been found to apply all the 5 types of AR inputs to form decision support data, while no model-oriented decision support systems has ever applied web camera content as the only AR input. AR data interaction was applied in every type of DSS to allow for interactive decision support. Representational models took only AR tracking data and user's data interactions as input to estimate the consequences of specific actions at certain locations. Optimization models have taken the user's AR data interaction as the only input to present the situation analysis. However, both the representational and optimization models also require the analysis of the current situation to refine their estimation and situation analysis. Therefore, it may be worth taking the contextual AR inputs to enhance the decision support in representational models, such as analyzing web camera content.

5.5. AR decision support data localization approaches

Nowadays, large-scale datasets provide abundant and heterogeneous information resources for all types of decision support systems while making information overload and information inconsistency critical challenges that hinder decision making (Roetzel, 2019). This issue is especially compelling for AR-based DSS due to the limited Field-Of-View (FOV). Visual clutter led by inappropriate visual arrangement and information filtering of the AR data visualization systems may also cause safety issues. The various AR input approaches provide new potential to help DSS efficiently filter relevant AR data according to the user's current contexts, so that the amount of data is reduced before the visualization phase. However, the arrangement and localization of visual elements constitutes another important research topic in the AR data visualization realm, aiming to reduce the discontinuity and inconsistency presented to end users. Therefore, this section analyzes the AR data localization approaches of all the collected samples.

Among all collected samples, the decision support data were mainly visualized with several typical AR visualization paradigms: situated visualization (White and Feiner, 2009b), in-situ AR visualization (Ens and Irani, 2017), and embedded visualization (Willett et al., 2017). According to definitions of these paradigms, AR data are integrated as an entire visualization or separated into individual data representation, localized at the environment where the data is collected or applied. Alternatively, the AR

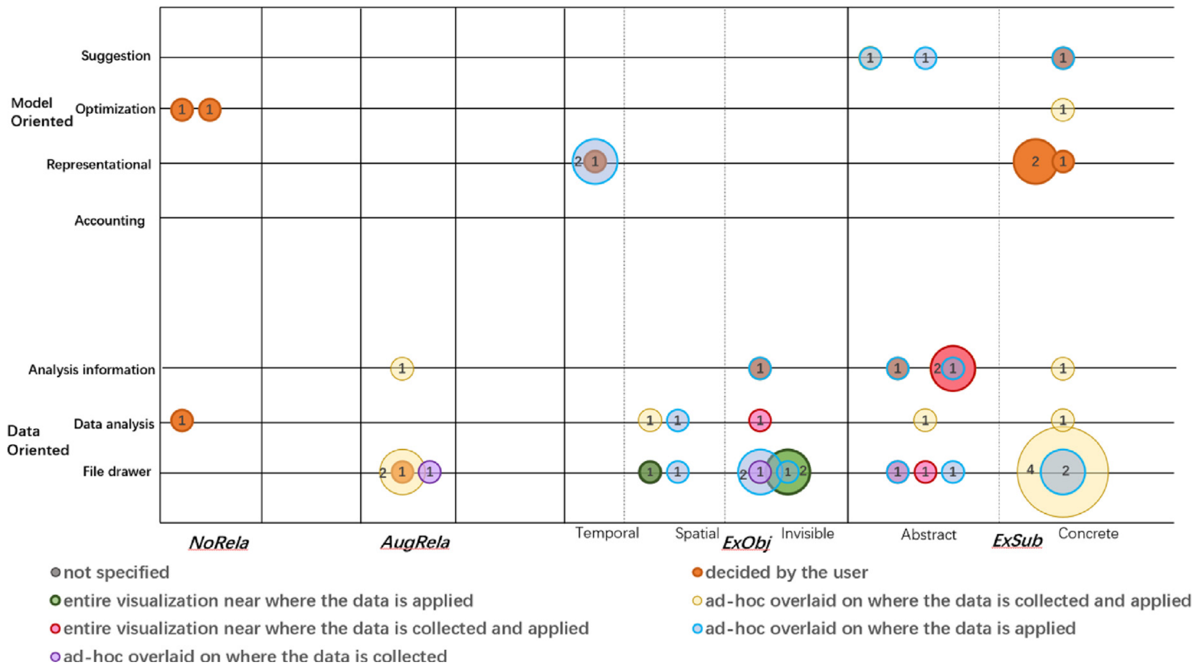

Fig. 9. Distribution of 6 types of AR decision-support data localization approaches: the *X* axis shows the AR data visualization categories (axis titles are abbreviations introduced in Fig. 3) according to the proposed AR data visualization taxonomy based on the data-reality relationships, and the *Y* axis shows the DSS category. The bubble label and size stands for the number of analyzed systems falling into each group. The bubble color stands for its data localization approach. The dashed line indicates the borders between sub-categories within the same AR data visualization category.

data may not be bound to specific physical environments but are directly localized according to the user's manipulations and preferences. Through sample analysis, the AR data localization approaches applied in the collected AR-based DSS samples showed specific associations with the decision data types and the AR data visualization types. Therefore, 6 types of AR data localization approaches are identified from the collected samples and are analyzed along the two dimensions of the AR data visualization taxonomy and the DSS taxonomy (Fig. 9), as follows:

- **Ad-hoc Overlaid on Where the Data is Applied:** Each AR data representation is overlaid on its corresponding physical referent involved with the decision-making questions.
- **Ad-hoc Overlaid on Where the Data is Collected:** each AR data representation is overlaid on its corresponding physical referent where the data is collected.
- **Ad-hoc Overlaid on Where the Data is Collected and Applied:** each AR data representation is overlaid on its physical referent that is involved in decision-making, in the situation where the data is also collected from the same physical referent.
- **Entire visualization near where the data is applied:** the entire visualization of AR data is placed at the corresponding decision-making context where the data is collected outside of this visualization context.
- **Entire visualization near where the data is collected and applied:** the entire visualization of AR data is placed at the corresponding decision-making context where the data is also collected from this visualization context.
- **Decided by the user:** the decision support data is not bound to any certain fixed physical environment but are placed by the user, either through moving fiducial markers or detecting arbitrary physical surfaces for AR visualization localization.

Fig. 9 shows how these AR data localization approaches are applied in different AR data visualization categories. Among the samples that visualized AR datasets without semantic data-reality relationships (*NoRela*), the AR data localization was all decided by the user. The situated visualization of entire datasets has not been applied by any of the samples that augmented specific physical referents with subjective AR understanding (*AugRela*). Regarding the two localization approaches that overlay individual AR data representation or the entire AR dataset on where the data is applied, the AR data is placed in relevant decision-making contexts or decision-relevant physical referents but may appear at a distance from the data sources. Thus, these two AR data localization approaches have only been found within the DSS samples that extend reality with additional visibility (*ExObj*) or external complementary knowledge (*ExSub*). In these scenarios where the sources of useful decision support data are located distant from the decision-relevant contexts, visualizing decision-support data with its proximity to the user or the decision-relevant contexts may cause less cognitive load for users than in-situ visualizing them over the data sources. This point may also be supported by the similar distributions (Fig. 9) of the user-decided AR data localization approach and the ad-hoc overlays of individual AR data representation on where the data is applied.

More importantly, the data localization approaches have also shown specific associations with the type of decision support data according to Fig. 9. According to Willett et al. (2017), the entire visualization of situated data is preferable to ad-hoc overlaying on individual physical referents when the visibility and accessibility of the entire dataset are crucial. This argument may explain why the situated visualization of entire datasets has only been found in data-oriented DSS: in contrast, model-oriented DSS place much less emphasis on the interpretation of the dataset. Instead, model-oriented DSS provide simulation and suggestions based on targeted decision-making problems, thus these higher-level decision support data are typically located with proximity to the decision-maker and the decision-relevant physical referents. By contrast, the AR data localization approach that overlays data on where it was collected may separate the decision-support data from the user and the decision-relevant context, thus it has only

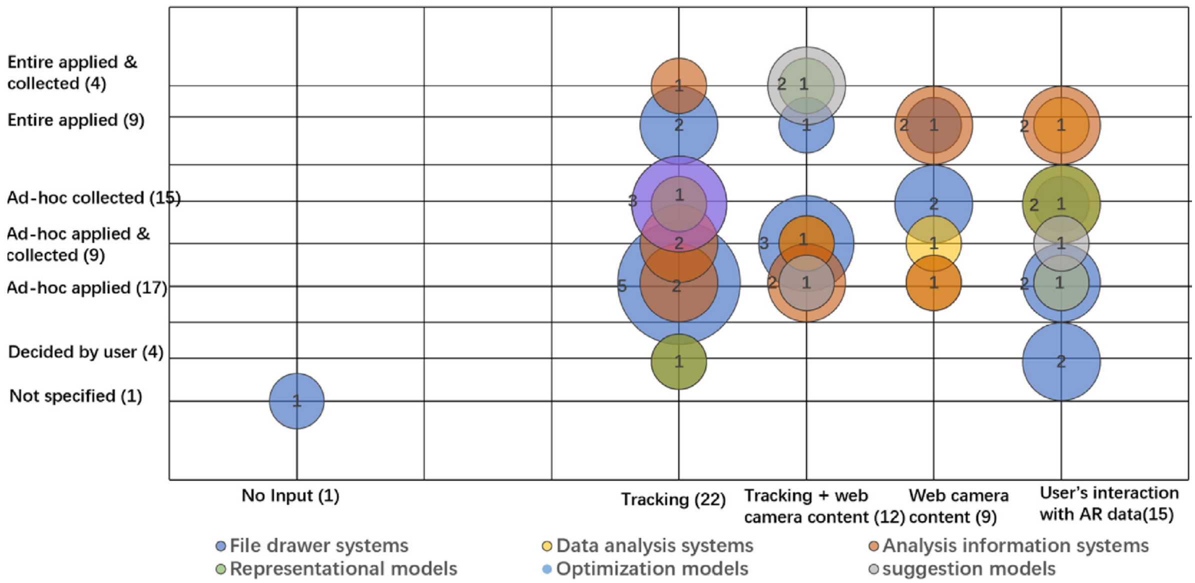

Fig. 10. How different AR input and localization approaches have been combined to visualize decision support data (The X axis shows the AR data localization approaches, and the Y axis shows the AR input categories; The bubble size stands for the number of analyzed systems falling each group. The bubble color stands for its application area.).

been found in a few file drawer systems that have the lowest data operations and analysis requirements. Therefore, the user may still be able to acquire the brief information conveyed by these file drawer systems by glancing from a distance at the data source (e.g., sensors). Among all AR data localization approaches, the most straightforward user-defined localization has also been the most widely applied approach, being found among all types of DSS categories. This tendency might be due to the critical decision-maker role of the end users. The most commonly applied AR data localization approach is ad-hoc overlaying AR data on where it is applied (17 samples). This AR data localization approach was applied in both data-oriented and model-oriented DSS that extended the reality with AR data visualization. This localization approach usually spatially maps the AR data with the decision contexts regardless of the data origin. Therefore, this approach stresses the semantic associations between the external visibility and knowledge and the decision contexts, based on which the decision support data or models can be clearly associated with the corresponding decision-relevant objects.

5.6. AR data input and localization approaches for decision support

It has been illustrated above that how different AR data input and localization approaches have been respectively applied to visualize decision support data. In most AR-based decision support systems, AR input categories could directly affect what extra information the decision engine could abstract from the user or physical environment to optimize decision relevancy and accuracy. On the other hand, different AR data localization approaches could affect how the data-reality relationships are presented to the user to assist their decisions. Therefore, analyzing how above AR data input and localization approaches are combined to enhance different decision support systems may reveal deeper insights of how AR techniques facilitate decision support from data retrieval to presentation.

Fig. 10 illustrates how the collected samples combined 5 types of AR input and 7 types of data localization approaches to enhance various decision support systems. Although Section 5.5 found that the user-defined AR data localization approach was widely applied in each DSS category, while it was missed from the samples taking web camera input for decisions. This pattern may have explained that one important role of webcam input for AR system is to automate the data localization according to the physical surroundings, which saves the users from manually adjusting where the data overlays. The latter automatic localization approach may allow for more flexibility and concentration for the decision maker, which suits the decision support scenarios where the user's both hands are occupied or their full attention is required to solve the decision questions, such as driving (Eyraud et al., 2015; Gomes et al., 2012) and fieldwork (Phupattanasilp and Tong, 2019). This figure clearly shows an obvious cluster in the combination between the ad-hoc AR data overlaying and the tracking input, which almost covers all DSS categories. This cluster indicates a typical metaphor of AR-based DSS that ad-hoc visualizes the decision support data with the proximity to where the data is collected or applied based on the AR tracking input.

Although the file drawer system is found to be the most widely applied DSS category that covers all types of AR input and localization approaches, Fig. 10 presents a gap of AR-based file drawer systems on the right-top corner, which indicates that no file drawer system takes user interaction as the input and localizes AR data as an entire visualization block. As it was discussed in Section 5.5, ad-hoc overlaying AR data over the physical contexts tend to stress more semantic data-reality associations compared to the entire visualization of AR data blocks. Meanwhile, according to Section 5.4, the user AR interactions are commonly input to file drawer systems for information filter aims. For the file drawer systems which rely on user's proactive interactions to filter information and present it with weak associations with the surrounding environment, AR visualization techniques may show very limited flexibility and context-awareness compared to the traditional portable computing devices, such as tablet and portable computers.

According to this gap, it can be conjectured that for those DSS which only provides relevant information to aid in decisions, the main advantages provided by AR visualization lie in either the flexibility brought by hands-free interactions and implicit contextual information input, or the explicit data-reality associations emphasizing brought by the ad-hoc mapping of the data chunks and relevant physical referents. Without these two unique advantages, the DSS may not obtain profound bi-directional contextual information exchange between the inner system and external

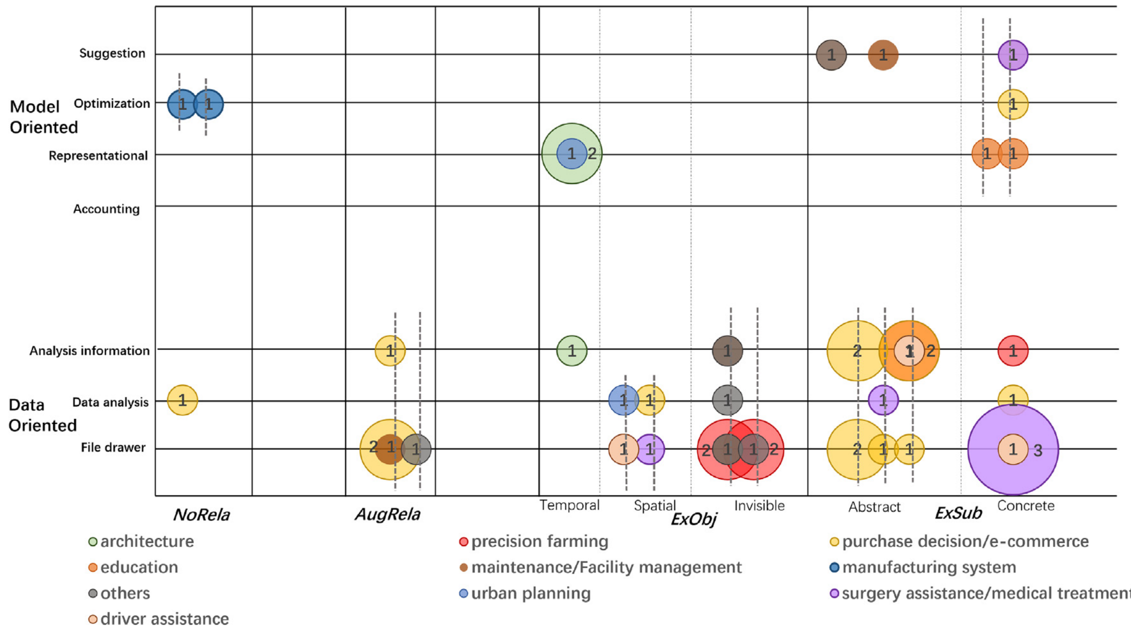

Fig. 11. Distribution of 9 application areas of the collected AR-based DSS samples: the X axis shows the AR data visualization categories (axis titles are abbreviations introduced in Fig. 3) according to the proposed AR data visualization taxonomy based on the data-reality relationships, and the Y axis shows the DSS category. The bubble label and size stand for the number of analyzed systems falling each group. The bubble color stands for its application area. The dashed line indicates the borders between sub-categories within the same AR data visualization category.

environment in an user-friendly manner. However, the essential contextual information may not only comes from the decision environment, but also from the decision-maker users. Therefore, even without such bi-directional environmental contexts exchange, AR visualization techniques may still bring unique advantages for more complex DSS by providing intuitive user interactions for user-centered contexts obtaining (e.g. ElSayed et al., 2016).

5.7. Application areas

AR data visualization has been applied for decision support in broad areas. According to the analysis of all 59 collected samples, their application areas have been classified into 9 categories: precision farming, purchase decision/e-commerce, manufacturing systems, maintenance/facility management, driver assistance, architecture, surgery assistance/medical treatment, urban planning, education, military, and others. To investigate how different types of AR-based decision support systems have been applied in these areas, the following sections discuss the distribution of samples within these areas, and how this distribution has changed over time.

5.7.1. Distribution

Fig. 11 illustrates the distribution of all 9 types of application areas based on the collected samples' DSS categories and AR data visualization categories. Each bubble in this figure stands for a group of samples that combine the X type of AR data visualization strategy and the Y type of DSS to support the decision in the area represented by its color (legend), and the bubble size indicates the number of samples falling into this group. By investigating this sample distribution, we may gain insights into how each type of AR-based DSS has been applied to different application areas.

AR-based DSS has been most often applied to support purchase decisions and e-commerce trading. Almost all samples applied in this area are data-oriented models. In addition, two types of AR datasets have been commonly applied to support purchase decisions: the subjective understanding about the products (*AugRela*) and the subjective external data as the extension to the purchase context (*ExSub*). By instantly visualizing the description, explanation, analysis, and recommendation of the products within the purchase context, these systems allowed customers to select and compare products much more easily. These data-oriented decision support systems only provide ubiquitous access to the product information and leave the decision tasks to the customers. By contrast, very few model-oriented decision support systems have been found to provide more direct decision support by highlighting the suitable products according to user-defined metrics (ElSayed et al., 2016). For such high-level decision support systems, clear explanations as to the recommendation and suggestions will be essential to increase user trust and system transparency (Nunes and Jannach, 2017).

Precision farming is the second common application of AR-based decision support systems. According to the distribution, all precision farming samples converge in the categories that visualize AR extensions to enhance the data-oriented decision support systems. 5 samples fall into the category of file drawer systems, and 3 samples are found to be the analysis information systems. As farmers usually need both hands available for work, instead of providing data analysis systems that rely on the farmers to frequently manipulate the data, file drawer systems and analysis information systems have been frequently applied to directly present relevant soil and crop data or the analysis of these datasets. In these file drawer systems, invisible data such as soil moisture, soil chemical properties, and temperature were initially visualized as an AR extension to support farming decisions on irrigation, fertilization, crop selection, etc. Analysis information systems superimposed the situated analysis such as historical crop yields and crop decease prediction over the user's contexts to support the on-site decisions. Making these precision farming data spatially aware allows the farmers and agronomists to make informed decisions during field trips. However, no model-oriented decision support systems have been found in the precision farming domain to provide more direct decision support, even though a large percentage of farmers are not equipped with enough professional knowledge to make accurate decisions in some complex contexts independently.

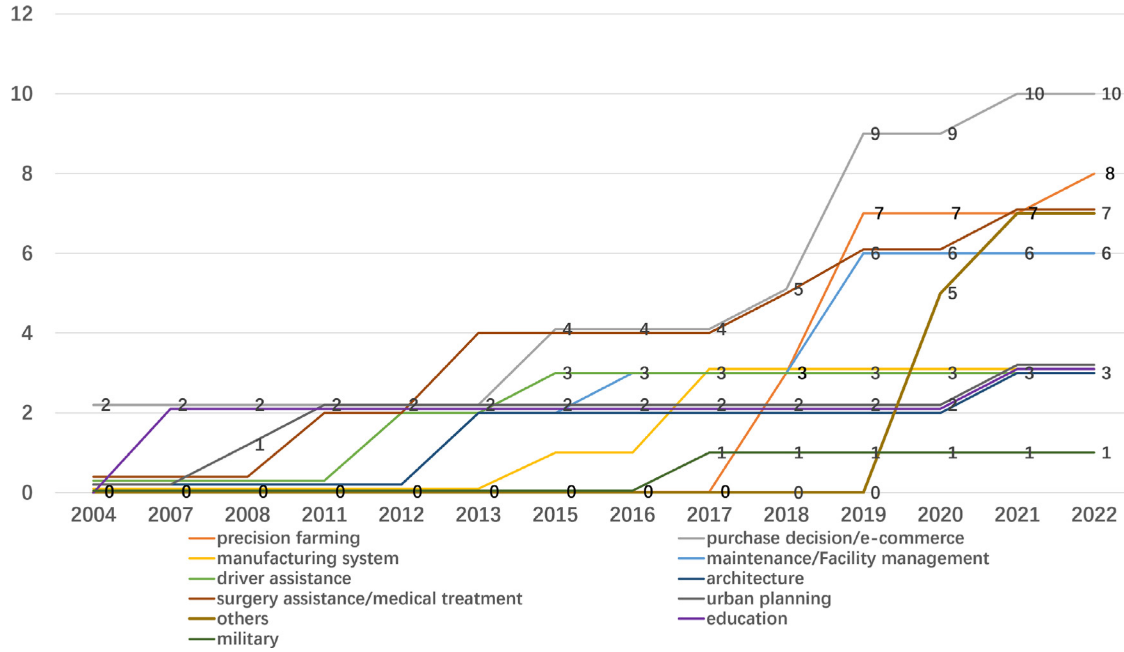

Fig. 12. Application areas of AR-based DSS over time: the *X* axis shows the years, and the *Y* axis shows the number of samples in each application area by year.

AR data visualization has also been frequently applied to support surgery assistance/medical treatment decisions. In this area, most samples are file drawer systems that visualize two types of AR extensions: the spatially extended objective data such as under-skin anatomical structures or the remote surgeon's hand gestures, and the extension with subjective concrete data such as AR highlights or markers on the affected parts and identified cancer areas. By highlighting certain affected parts and anatomical structures under investigation, the surgeons may get a clearer view of the surgical anatomy and make accurate and efficient decisions during surgery. Spatially extended AR data have not only been applied to in-situ visualize the under-skin anatomy, but more importantly, have played essential roles in telemedicine by visualizing the remote surgeon's gestures. These surgery assistance systems are generally targeted at expert users such as surgeons and therapists who are assumed to be equipped with enough professional knowledge to make crucial decisions. Therefore these systems provided minimal interference to the application context, leaving the vital decision to the medical professionals. Also, the surgical process often requires the surgeons to concentrate on the operations with both hands. Therefore, file drawer systems have been most commonly applied to provide medical decision support with few data interactions.

Maintenance/facility management as one of the common application areas of AR-based DSS shows a more scattered distribution as Fig. 11 illustrates. File drawer systems, analysis information systems, and suggestion models have all been applied to support decisions in maintenance work by superimposing facility descriptions, sensor data, facility analysis, maintenance guidance, and AR marks over their physical contexts. Among these datasets, the facility descriptions/analysis and sensor data all work as data-oriented decision support that strengthens the workers' understanding of the environment under maintenance. In contrast, suggestion models analyze the environment situation and facility properties to directly generate maintenance guidance for the maintainers. Therefore maintainers can focus on the actual maintaining operations with the anticipatory guidance. These datasets vary in complexity and decision support levels, giving both skilled and unskilled maintenance workers options to select flexible decision support according to their levels of expertise. Similar to the decision support in medical treatment and precise farming, maintenance work often also requires both hands to complete tasks; thus, no data analysis systems have been found in this area.

As the most common type of model-oriented DSS among all collected samples, the representational model works as an important strategy to support architecture, urban planning, and education. One common type of representational model visualizes the estimated consequences of specific actions by in-situ superimposing the predicted future of the current decision-making context as an AR extension. These extended future estimations have been applied to visualize architecture and urban planning blueprints on site, therefore helping designers to identify design flaws early.

Aside from the application areas mentioned above, AR-based decision support systems have also been found in military training, driving assistance, and other daily decision-making tasks. According to the above discussion about the application distribution of the AR-based decision support in multiple areas, each application area seems to have different requirements in terms of the complexity and visualization strategies of the decision support datasets. Based on the investigation on these various requirements, some guidelines on the future design of AR-based decision support systems in several key areas have been indicated in Section 6.

5.7.2. Development over time

Fig. 12 shows the distribution of the AR-based DSS in the 9 application areas over time. Purchase decision/e-commerce is currently the most common application area of AR-based DSS, and the samples in this area have continued to increase rapidly in recent years. Precision farming decision support systems with AR visualization strategies have only appeared since 2017, showing drastic growth speed after that and ranking in the top two by 2022. Surgical assistance and maintenance work is also a common application area of AR-based decision support systems. In recent years, the application of AR-based decision support systems is focused on these 4 main areas: purchase decision, precise farming, surgical assistance, and maintenance work, while the other application areas have become much less widespread since 2017. Therefore, it seems that the development of AR-based decision support systems has entered the stage of converged research on specific applications that have shown significant potential after the initial attempts in diverse areas.

6. Discussion and future directions

This section provides a high-level discussion of the findings observed from the sample analysis provided above, which analyzes the potential factors that led to the specific development tendency of AR-based DSS. After discussing these findings, several future directions are proposed with the support of relevant AR-based DSS examples, which may provide a guideline to inspire the development of this research area.

6.1. Discussion

According to our analysis of the collected samples, the development of each type of AR-based decision support system can be mainly affected by 3 factors: the difficulties of developing a specific type of AR-based decision support system; whether the main advantages of AR data visualization are essential to facilitate the decision-making process; the development of the relevant contextual data collection technologies required by certain types of AR-based decision support systems.

First, the difficulties associated with developing any AR-based decision support system depend on the complexity of the specific system type and its restrictions on data-context relationships. For example, file drawer systems only provide online access to specific data items, thus requiring the least development effort and having the least restrictions on the data-context relationship. This means that it is relatively straightforward to integrate file drawer systems with AR data visualization, and file drawer systems have been found to apply nearly all types of AR data visualization strategies to support decision making (Fig. 4). By contrast, model-oriented decision support systems require a more complex design of specific models. All model-oriented decision support systems need to analyze and study the user's specific actions or the current situations to provide subjective estimation, analysis, and suggestion, which have massively restricted the data-context relationships. The effect of these restrictions is reflected by the distribution of model-oriented DSS samples (Fig. 4). They mostly appear in the zone where AR has been applied to extend the reality with subjective data (Section 4.8). Therefore, the sample analysis indicates that both the complexity of the decision support system itself and its restrictions on the data-context relationship may have an effect on the development of different types of AR-based DSS.

Second, the trends in each type of AR-based DSS are affected by the degree to which AR data visualization can bring advantages over other visualization approaches. As is mentioned in Section 1, common advantages of AR data visualization include hands-free interactions, instant data superimposition, spatially-mapped AR data for bi-augmentations between physical and virtual spaces (Lee et al., 2008), and context-aware data visualization. To motivate the use of AR-based visualization within DSS, it is necessary that these common advantages must bring significant enhancements in terms of decision efficiency, accuracy, or user satisfaction. Generally, data-oriented DSS tend to focus more on the data visualization and interaction technologies when compared to model-oriented DSS, given their differences in terms of the data volume and complexity provided to the end-users. Accordingly, data-oriented DSS seem to be confronted with more challenges to reduce the cognitive load, analysis time, and domain knowledge required for an end-user to make a decision based on a series of potentially complex data provided by the system. These challenges form the motivation for seeking potential solutions from novel visualization tools, while the typical advantages of AR data visualization contribute to the emergence of AR-based data-oriented DSS research. By contrast, model-oriented DSS usually keep the context understanding, data analysis, and computations within the system's black box and provide the end users with the final result. According to Fig. 9, it is the users who typically decide location of the superimposed model-oriented decision support data. Therefore instant data superimposition and hands-free interaction are more significant for model-oriented DSS than the spatial mapping of context-aware data. AR-based model-oriented DSS are thus mainly applied to time-sensitive decision support tasks that require on-site decision-making (Fig. 11), such as manufacture, shopping assistance, surgery assistance, precision farming, etc. Because time is a critical factor for such systems, applying AR data visualization to instantly superimpose decision support data within the user's field of view may save them from switching focus from the decision context to the traditional desktop or mobile phone DSS interfaces. In addition, the diverse data visualization requirements of each type of data-oriented decision support system also lead to differences in their popularity. For example, as is shown in Fig. 6, analysis information systems have been much more commonly applying AR to visualize decision support data compared to data analysis systems. This tendency has continued through to 2022, despite the fact that analysis information systems require more complex data than data analysis systems. One important reason might be their different requirements for contextual data. According to Alter's description of these two types of decision support systems (Alter, 1977), a generalized data analysis system is relatively context-free and leaves the analysis work to the users by allowing them to operate on the provided data. In contrast, analysis information systems usually require external data and multiple datasets collected from the decision-making context to provide a thorough analysis report. Also, as is pointed out in Section 4.6, among all collected samples most analysis information systems have been found to provide analysis reports of the user's context as subjective extensions, in which the analysis reports are typically provided based on the user's historical actions and contextual data collected from the user's surroundings. Therefore, the motivation to adopt AR data visualization for different types of DSS is strongly affected by how relevant the advantages of such visualizations are to the specific use case.

Third, all types of DSS massively rely on different types of datasets to provide decision support. Thus the development of the necessary data collection techniques will undoubtedly facilitate the development of relevant decision support systems. As is pointed out in Section 5.1, objective AR data extensions have become increasingly popular for data-oriented decision support systems. Additionally, visualizing initially invisible data as an objective extension (*ExObj-Invisible*) to the physical context has been a more common decision support strategy in recent years compared to temporal or spatial extensions of the current context. Moreover, as is shown in Fig. 4, among the collected *ExObj-Invisible* samples, most samples have been found to visualize sensor data. Based on these distributions and tendencies, it can be concluded that sensor data has been more frequently applied for data-oriented decision support systems. As is inferred in Section 5.3, this trend might have been caused by the popularization of IoT and WSN techniques, which makes sensor data much more ubiquitous and accessible. Owing to the increased accessibility of sensor data, context-aware AR systems and decision support systems based on the contextual parameters have become more popular in recent years. For example, according to the analysis in Section 5.7, precision farming and maintenance/facility management are two key application areas that commonly utilize sensor data for decision support, and have shown significant growth trends in recent years.

6.2. Future directions

6.2.1. Applying AR data visualization for model-oriented decision support systems

The analysis of all the AR-based DSS samples have shown the research gap in AR-based model-oriented DSS: very few of the collected samples have been found to apply AR data visualization for model-oriented decision support. For the decision contexts that involve vital decisions, such as medical treatment and driving assistance, the designers assume the users are equipped with enough professional knowledge to make more accurate decisions than the current systems. However, in several key application areas, providing higher-level decision supports may allow non-expert users to instantly make accurate decisions even though they lack sufficient knowledge to analyze the decision alone. For example, precision farming aims to increase agricultural management efficiency by providing expert knowledge for farmers (Phupattanasilp and Tong, 2019). Accordingly, providing higher-level decision supports such as crop yield optimization schemes or fertilizer suggestions will allow the farmers to efficiently make accurate decisions during field trips. However, the collected samples in this area are still limited in terms of data-oriented decision support. As is discussed above, one reason for the lack of AR-based model-oriented DSS might be the difficulty of developing such complex systems. However, several model-oriented decision support systems (Perini and Susi, 2004; Navarro-Hellín et al., 2016; Thorp et al., 2008) have been found to support precision farming with prediction, estimation, simulation, and advisory assistance. Visualizing these datasets on the farm using AR techniques to make them instantly spatial aware for the farmers will bridge the gap between indoor desktop analysis and in-field decisions, although integrating this high-level decision support into the physical context with AR intuitively and ubiquitously is still a challenge. Similarly, this research gap also exists in other application areas such as facility management and e-commerce. Therefore, more exploration on visualizing higher-level decision support with AR strategies will potentially boost the development of precise farming, facility management, e-commerce, and related industries.

6.2.2. Utilizing environmental sensor data for on-site decision support

As is discussed in Section 6.1, the recent trend of visualizing previous invisible sensor data as an extension to the decision-making context might have been affected by the popularization of wireless sensor networks, which allows ubiquitous access to real-time sensor data. By recording and analyzing these environmental sensor measurements, the decision support systems can thoroughly understand the targeted environment and form accurate decision supports that suit the prevailing situation. This strategy has shown significant advantages for on-site decision-making tasks in dynamically changing environments where these environmental changes can significantly affect decisions, such as precision farming, facility management, urban planning, etc. Compared to traditional sensor data monitoring tools that provide centralized visualization of sensor data on screens, AR tools allow the system to elaborate the decision-making context intuitively by visualizing the environmental sensor measurements and spatially mapping them to the local environment. Therefore, a recent trend has been that data-oriented decision support systems visualize these sensor data with AR tools in the local context.

Moreover, apart from visualizing these invisible environmental parameters, including them in the computation and analysis processes of model-oriented decision support systems will also be a potential future direction. One potential example are suggestion models that generate suggested actions based on the analysis and calculation of current environmental sensor measurements according to predefined decision rules (Zheng et al., 2022a). Alternatively, in representational models, these environmental parameters can also be applied to estimate the consequence of specific actions in advance to avoid losses caused by suboptimal decisions. In these potential scenarios, environmental sensor data also allow the AR systems to be context-aware enough to appropriately locate these decision-support data at relevant parts of the context on suitable occasions. However, since model-oriented DSS may require a more condensed and integrated visualization of the decision support data, efficiently filtering the heterogeneous sensor data and arranging the visual presentation to serve the optimization and suggestion models will be an interesting challenge.

6.2.3. Contextual AR inputs to model-oriented decision support systems

According to the discussion in Section 5.4, web camera content analysis, as one important AR input to help systems understand the decision-making context, has only rarely been applied to provide higher-level decision support. However, this gap does not mean a lack of motivation. For example, as is pointed out in Section 5.4, although optimization models have tended to only take the user's AR data interaction as the input, this type of system also needs to study and describe the current situations. Some important contextual data may not be easily perceived from the user's interactions, such as the user's current environment, focus, and current AR information load over their spatial surroundings. Perceiving these data utilizing the web cameras would help the system filter and present more relevant decision support data more appropriately.

Although fiducial marker tracking has also been commonly applied to track the user's focal objects for relevant data superimposition (Zhu et al., 2004; Segovia et al., 2015; Marques et al., 2019b), it cannot be applied in large-scale unprepared environments. Therefore, web camera content may be a suitable contextual AR input for decision-making tasks in such environments. It has been applied in several data-oriented decision support systems to analyze the user's focus and surrounding context. For example, by recognizing the food and crops within the user's field of view, AR systems provided certain data items relevant to recognized objects (Phupattanasilp and Tong, 2019; Waltner et al., 2015). Another example is that of smart home suggestions, where suggestions based on the type of detected focal objects, along with relevant datasets, can be used to provide higher-level decision supports to help achieve goals more directly (Zheng et al., 2022a).

Due to the limited time and focus during field trips, users may not take a long time analyzing the decision question and making prudent decisions. In this situation, web camera contents may work as an essential input to record the field trip decision-making process for further analysis. Based on prior works that apply outdoor AR systems to provide on-site decision support during field trips (Phupattanasilp and Tong, 2019; Xi, 2018; Zheng and Campbell, 2019), after finishing the on-site tasks, the images and videos captured by the web camera during the field trip can be potentially recorded and uploaded for further in-depth analysis and computation. In this way, the web camera content can be reused as thorough historical records of the decision-making sites, allowing for more complex and time-consuming decision supports after the field trip has been completed. Therefore, contextual AR inputs such as web camera content can potentially be applied for model-oriented decision support systems to provide more accurate suggestions, estimations, and situation analysis by analyzing the user's current focus and recording field-trip captures.

6.2.4. Localizing multi-dimensional AR decision support data about individual physical referents

As Section 5.5 discussed, the AR data localization approaches of the collected AR DSS samples are either ad-hoc superimposition of individual data representations or the visualization of entire datasets. The former approach mostly overlays a single type of decision support data on individual physical referents. Allowing objects in the real world to have data directly associated with them. In contrast, the latter approaches normally provide the situated visualization of the decision support data about the entire decision-making context. However, in many decision-making contexts, the user may need to combine multiple types of relevant data to support the decisions about an individual physical referent. One good illustration may be the *AR-IoT* (Phupattanasilp and Tong, 2019) and *STARE* (Zheng et al., 2022a) interfaces which overlaid multiple relevant sensor data and decision support data over individual recognized focal objects to support instant decisions. In complex decision contexts where the data sources are heterogeneous, or the decision questions are indistinct, the embedded visualization of multi-dimensional decision support data assembly may lead to less cognitive load for the users compared to other common AR data localization approaches discussed in Section 5.5. However, more challenges exist in relevant data filtering and visual element arrangement to spatially visualize such multi-dimensional data over individual physical referents without information overload. To filter the multi-dimensional data that are relevant to the physical referents, the system should construct complex semantic data-reality associations in advance. In the *AR-IoT* and *STARE* examples, the data-reality associations were manually constructed to associate multiple types of IoT data with different types of decision objects. However, to increase scalability, more generalized data-reality associations should be constructed for various decision-making contexts to associate various available data and possible decision-relevant objects within this context. Machine Learning and Deep Learning techniques may be utilized to automate the process of creating and deriving associations, thus facilitating the revolution of AR data visualization towards the future ubiquitous big data decision support.

6.2.5. The explorations of AR-based suggestion models and past visibility reproduction for decision support

By comparing the sample distribution (Fig. 4) and the AR data visualization taxonomy tree (Fig. 3), we found that a few types of AR data visualization strategies have rarely been applied for decision support. Among these, the AR extensions of suggestions and past visibility are both worthy of further exploration.

Suggestions, as one type of subjective AR extension, have only been visualized in two AR DSS samples to support teaching decisions (Pan et al., 2021) and smart home decisions (Zheng et al., 2022a). The *"suggestions"* referred to in the proposed AR data visualization taxonomy particularly indicate *"what to do"* under certain circumstances. Such suggestions usually have low dataset complexity while only being effective in highly relevant contexts. Therefore, visualizing a *"what to do"* suggestion typically requires a thorough analysis of the decision contexts, especially when there are no predefined tasks or specific option lists available. This means that the system needs to infer the user's goal and the current situation, and then work out the possible solution. A good example of this type of suggestion is the AR library service system that infers the user's reading requirements from the scanned assignment page, and then provides relevant library resources (Hahn, 2012). When applied for decision support, the provision of *"what to do"* suggestions will require even more complex data input and decision rules, such as the multi-dimensional data-object associations constructed in the *STARE* system (Zheng et al., 2022a). According to the discussion in Section 6.1, the complexity of such systems might be the main reason for this gap. However, the *"what to do"* suggestions will potentially increase the decision accuracy and efficiency for numerous decision-making scenarios. For example, superimposing these suggestions using the AR headsets for decision makers who are occupied by the task at hand allows them to concentrate on their current work while making instant decisions. Compared to traditional suggestion models that require users to input queries and select parameters on a phone or computer to learn the suggested actions, AR may provide a distraction-free and instant solution to visualize the *"what to do"* suggestions in an appropriate time and context.

Visualizing past situations is not something that has been applied thus far in AR-based decision support systems, although it is something that has significant potential for certain application types. Visibility of future situations has been used in construction, to in-situ visualize architectural blueprints on construction sites to support planning decisions (Olsson et al., 2012). In a similar way, visibility of past situations may also facilitate decisions for architectural restoration tasks. By in-situ visualizing the original appearance of damaged or old buildings, architects could easily create a restoration plan using the comparison between the original and current building appearance. Another potential decision-support application of past visibility might be in-situ historical flood visualization on a construction site. Historical flood records are always an important resource for future flood risk estimation, and 3D visualization of future flood prediction has also been applied to support building risk assessment in the planning phase (Amirebrahimi et al., 2016). Therefore, such historical flood data could be in-situ visualized to support architectural decision making for flood-prone areas.

6.2.6. Explainable decision support through AR data visualization

In order for decision support systems to be considered trustworthy, transparent and effective, they should be able to provide explanations for the advice that they provide (Nunes and Jannach, 2017; Gershman et al., 2015). This has prompted substantial research on explainable decision support and explainable artificial intelligence (XAI). In decision support systems, different forms of visualizations such as graphs have been commonly applied to convey explanatory information to users (Nunes and Jannach, 2017). However, the collected AR-based DSS samples tend to lack this type of explanation. This may be due to the relative immaturity of the AR-based DSS area and the limited number of AR-based advice-giving systems. However, this does not mean that this is not an important consideration within this research area.

Explanations are especially important for time-sensitive decision tasks in dynamically changing contexts. In such decision contexts, to generate explainable advisories for front-line workers or field-trip decision-makers, the system may need to visualize the relationships and inferences between knowledge objects, including environmental variants happening in the decision maker's surroundings. Compared to visualizing these contextual associations on laptops or mobile phones, AR data visualization may enhance how the information is conveyed in a number of novel ways. Apart from instantly superimposing text and voice explanations for the system-generated advisories in relevant decision contexts, explanation graphs may be constructed by extracting contextual data from the user's surroundings and spatially mapping these to the physical entities (Lee et al., 2008). By highlighting the different physical entities in the decision contexts that affect the decisions, and visualizing their interrelations, the decision maker may intuitively perceive how the physical entities and events happening in their surroundings interfere with the decision-making process. This process allows even non-expert users to understand the justifications and logic behind the system-generated advisories with reduced cognitive load and domain knowledge, which may provide new potential for the explanations of different aims including education, persuasiveness, transparency, trust, efficiency, satisfaction, etc.

7. Conclusion

This paper proposed an AR data visualization taxonomy based on the semantic relationships between the AR data and context. According to this taxonomy and the DSS taxonomy proposed by Alter, 59 AR-based decision support samples have been classified and analyzed from the following aspects: the distribution and development tendency of these samples, the tendency of applying different types of AR data visualization strategies to support decision making, the tendency of different types of decision support systems to apply AR data visualization, the different types of AR inputs for decision support systems, the AR data localization approaches applied for decision support systems, the distribution, and tendency of common application areas. Based on the sample analysis from these aspects, multiple future guidelines and research gaps in this area have been pointed out.

To facilitate the future development of the AR-based DSS area, researchers should apply more standard evaluation criteria to evaluate how has a given AR interface affected the decision comfort and decision support satisfaction achieved by the system-generated decisions and explanations for different groups of targeted decision-makers. Based on such evaluation results, the evolution of AR decision support interfaces will bring more profound enhancements to the decision support realm. In a world that is now data-rich but time-poor, better decisions could be made if the right decisions support tools were available in situ. The taxonomy demonstrated in this paper offers a way to explore this new field, allowing both experts and users to understand data visualizations within AR.

It is essential to give language to AR-based DSS developers to understand whether the information presented has an intrinsic relationship with reality. Furthermore, it is critical to decide if that information can be used to extend the reality or can add context to understand a decision. This taxonomy, when applied to decisions support systems, offers a novel approach to helping mentally scaffold development in this new field for the future.

CRediT authorship contribution statement

Mengya Zheng: Conceptualization, Methodology, Writing – original draft. **David Lillis:** Writing – review & editing. **Abraham G. Campbell:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Ethical Approval

This study does not contain any studies with human or animal subjects performed by any of the authors.

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