Developing an Augmented Reality Visual Clutter Score Through Establishing the Applicability of Image Analysis Measures of Clutter and The Analysis of Augmented Reality User Interface Properties

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ABSTRACT

Augmented reality (AR) is seeing a rapid expansion into several domains due to the proliferation of more accessible and powerful hardware. While augmented reality user interfaces (AR UIs) allow the presentation of information atop the real world, this extra visual data potentially comes at a cost of increasing the visual clutter of the users' field of view, which can increase visual search time, error rates, and have an overall negative effect on performance. Visual clutter has been studied for existing display technologies, but there are no established measures of visual clutter for AR UIs which precludes the study of the effects of clutter on performance in AR UIs. The first objective of this research is to determine the applicability of extant image analysis measures of feature congestion, edge density, and sub-band entropy for measuring visual clutter in the headworn optical see-through AR space and establish a relationship between image analysis measures of clutter and visual search time. These image analysis measures are specifically chosen to quantify clutter, as they can be applied to complex and naturalistic scenes, as is common to experience while using an optical see-through AR UI. The second objective is to examine the effects of AR UIs comprised of multiple apparent depths on user performance through the metric of visual search time. The third objective is to determine the effects of other AR UI properties such as target clutter, target eccentricity, target apparent depth and target total distance on performance as measured through visual search time. These results will then be used to develop a visual clutter score, which will rate different AR UIs against each other.

Image analysis measures for clutter of feature congestion, edge density, and sub-band entropy of clutter were correlated to visual search time when they were taken for the overall AR UI and when they were taken for a target object that a participant was searching for. In the case of an AR UI comprised of both projected and AR parts, image analysis measures were not correlated to visual search time for the constituent AR UI parts (projected or AR) but were still correlated to the overall AR UI clutter. Target eccentricity also had an effect on visual search time, while target apparent depth and target total distance from center did not. Target type and AR object percentage also had an effect on visual search time. These results were synthesized into a general model known as the "AR UI Visual Clutter Score Algorithm" using a multiple regression. This model can be used to compare different AR UIs to each other in order to identify the AR UI that is projected to have lower target visual search times.

Developing an Augmented Reality Visual Clutter Score Through Establishing the Applicability of Image Analysis Measures of Clutter and The Analysis of Augmented Reality User Interface Properties

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GENERAL AUDIENCE ABSTRACT

Augmented reality is a novel but growing technology. The ability to project visual information into the real-world comes with many benefits, but at the cost of increasing visual clutter. Visual clutter in existing displays has been shown to negatively affect visual search time, error rates, and general performance, but there are no established measures of visual clutter augmented reality displays, so it is unknown if visual clutter will have the same effects. The first objective of this research is to establish measures of visual clutter for augmented reality displays. The second objective is to better understand the unique properties of augmented reality displays, and how that may affect ease of use.

Measures of visual clutter were correlated to visual search time when they were taken for the augmented reality user interface, and when they were taken for a given target object within that a participant was searching for. It was also found that as targets got farther from the center of the field of view, visual search time increased, while the depth of a target from the user and the total distance a target was from the user did not. Study 1 also showed that target type and AR object percentage also had an effect on visual search time. Combining these results gives a model that can be used to compare different augmented reality user interfaces to each other.

Dedication

I would like to dedicate this work to my late father, without whose guidance I would never have pursued a PhD in the first place. While he may not have got to see me complete my PhD, I know he would be proud.

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I would like to acknowledge the contributions of my mother and brother, as without their continued support this work would not have been possible. I would like to especially thank my fiancé, for her support, editing abilities, and statistical knowledge, all of which was essential to this work as well.

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1 Introduction

1.1 Problem Statement

Augmented reality (AR) is a rapidly growing technology that is seeing use in an increasing variety of domains and applications such as manufacturing [1], construction [2], military [3], and healthcare [4]. This proliferation of AR means an increase in AR user interfaces (UIs) and an urgent need for better methods of designing and evaluating these AR UIs, as well as understanding what aspects AR UIs affect user performance differently from traditional UIs.

One problem that has been extensively studied in traditional visual displays is that of visual clutter and its effect on human performance. Clutter is detrimental to the performance of traditional interfaces; it leads to errors, and increases time in finding objects of interest, increases time for decision making, and increases mental workload. Addressing this is especially important for AR UIs as AR is still a novel technology to most and adoption of this technology could be hindered by UIs that negatively affect performance. The inherent differences between AR UIs and non-AR UIs compound this issue, as currently there are no tools that look at all aspects of an AR UI holistically and evaluate it as such. Further, AR user interfaces offer inherently different experiences than traditional interfaces, since they overlay digital information onto the real world and often require users to verge (and in some displays accommodate) to information presented at different distances. In many AR use cases, users must visually switch between both the real world and the digital domain for needed information while simultaneously having both types of visual stimuli in their field of view. This mixture of real and digital objects may affect performance more than traditional visual display, and the relationship between visual clutter and performance needs to be quantified in order to better design AR UIs going forward.

AR UIs are more complex than their 2D counterparts as they introduce new perceptual phenomenon such as UI elements presented at different apparent depths and thus potentially having an AR UI with elements existing at multiple apparent depths (and associated with important real-world referents at varying real-world distances). Because of this, other variables will need to be explored such as the location of a target with the AR UI, as well as the clutter of the target, whether or not the target is projected or AR, the ratio of AR objects to projected objects in an AR UI, and the number of planes that comprise the AR UI.

1.2 Research Objectives

The purpose of this work is to determine the applicability of extant image analysis measures of visual clutter to AR UIs, and to create an algorithmic relationship between image analysis scores of visual clutter and AR UI properties to performance as measured through visual search time. Much work has gone into the analysis of visual clutter in traditional displays, but given the relatively new nature of augmented reality, the applicability of these measurement techniques is unknown. Therefore, the objectives of this work are:

1) Apply extant image analysis measures of visual clutter to the head-worn AR space and establish a relationship between image analysis scores of clutter and performance through the metric of visual search time. Use this relationship to develop a visual clutter score algorithm.
2) Examine the effects of AR UIs comprised of multiple apparent depths on visual search time and integrate the results in the visual clutter score algorithm.
3) Determine the effects of other AR UI properties such as target clutter, target eccentricity, target apparent depth and target total distance on performance as measured through visual search time. Integrate the results in the visual clutter score algorithm.

When taken together these studies provide an insight into factors that may affect visual search time in AR UIs and will form the basis of an initial algorithm to evaluate AR UIs in the context of expected performance through the measure of visual search time.

1.2.1 Objective 1

Apply extant image analysis measures of visual clutter to head-worn optical see-through AR UIs and establish a relationship between image analysis scores of clutter and performance through the metric of visual search time.

This study determines how to apply extant image analysis measures of visual clutter to optical seethrough (OST) head mounted (HMD) augmented reality (AR) displays, in conjunction with other factors that may affect visual search time such as the percentage of AR objects compared to projected objects in an interface, and the type of object a user is searching for (projected or AR). Extant image analysis techniques of feature congestion, edge density, and sub-band entropy are specifically chosen to quantify clutter, as they can be applied to complex and naturalistic scenes, as is common to experience while using an AR UI. The end goal of this study is to develop an algorithm capable of predicting user visual search time for a given target in a given AR UI.

Study 1 is designed to answer the following research questions:

RQ1. Can extant image processing techniques for measuring visual clutter (Feature Congestion, Sub-Band Entropy, and Edge Density) characterize visual search task performance as measured through visual search time in AR?

RQ2. How do different levels of clutter affect visual search time in AR-based visual search tasks?

RQ3. Are there differences in visual time between locating a projected or virtual object?

RQ4. How do differing ratios of projected objects to AR objects in an AR UI affect visual search time?

1.2.2 Objective 2

Apply extant measures of visual clutter to head-worn optical see-through AR UIs with AR UI comprised of planes of visual targets presented at multiple apparent depths and adjust the AR UI Visual Clutter Score Algorithm to account for any effects caused by multiple planes.

Study two extends study one by placing visual targets at different apparent depths, since in optical see-through (OST) head mounted (HMD) augmented reality (AR) displays, information may be presented at several different apparent distances from the user. This is further complicated by a target being able to appear in any of the AR UI planes. This study then explores how the visual clutter of the AR UI, different combinations of UI planes of differing apparent distances, and the target object apparent distance impact visual search time. Post hoc analysis also investigates the number of AR UI planes and the effect of target clutter on response time. The goal of this study is to develop an algorithm capable of predicting user visual search time for a given target in a given AR UI.

Study 2 is designed to answer the following research questions:

RQ5. Can extant image process techniques for measuring visual clutter (Feature Congestion, Sub-Band Entropy, and Edge Density) be applied to AR UIs with multiple planes?

RQ6. How do different target apparent depths and the number and apparent depths of AR UI planes affect participant visual search time in AR-based visual search tasks?

1.2.3 Objective 3

Apply extant measures of visual clutter to an AR UI comprised of three-dimensional objects at varying apparent depths from the user, and better characterize the effects of target eccentricity, target apparent depth, target clutter, and target total distance on visual search time. Refine AR UI Visual Clutter Score Algorithm to correlate with visual search time in these types of tasks.

Study three expands on studies one and two, exploring how visual clutter of the AR user interface (UI), the clutter of a target object the user is searching for, as well as target location affect visual search time. This work can be used to refine the AR UI Visual Clutter Score Algorithm.

Study 3 is designed to answer the following research questions:

1) RQ7. Can extant image processing techniques for measuring visual clutter (Feature Congestion, Sub-Band Entropy, and Edge Density) correlate with visual search time in an AR UI of more than 3 UI planes comprised of 3D objects?
2) RQ8. How do different levels of clutter affect visual search time in an AR UI of more than 3 UI planes comprised of 3D objects?
3) RQ9. Given an AR interface, can we create an algorithm capable of rendering a relative rating of visual clutter that allows comparing different AR UIs with respect to visual search times?

Table 1. Summary of studies

	Study 1	**Study 2**	**Study 3**

Objective	Apply measures of visual clutter to the head-worn optical see-through AR space	Determine the effects of AR UI apparent depths on an AR visual search task.	Determine the effects of clutter on 3d interfaces. Characterize the effects of other AR UI properties on visual search time
Research Questions	Do extant image processing techniques for measuring visual clutter correlate with visual search time in AR?	Do extant image process techniques for measuring visual clutter correlate with visual search time in an AR UI with different apparent depths	Do extant image processing techniques for measuring visual clutter correlate with visual search time in an 3D AR search task with objects of differing apparent depths
	Do different levels of clutter correlate to visual search time in an AR-based visual search tasks?	Do different object depths correlate to visual search time in an AR-based visual search task?	Do different levels of clutter correlate to visual search time in an 3D AR-based visual search task?
	Is there a difference between locating a projected or AR object?		Given an AR interface, can we create an algorithm that gives a single number rating estimate of visual clutter for comparing different AR UIs to each other?
Dependent Variable	Visual search time	Visual search time	Visual search time
Independent Variables	Clutter levels (Low, Medium, High), AR Object % (25%, 50%, 75%), Target Type (projected or AR)	Clutter levels (Low, High), AR UI Configuration (2m, 4m, 6m, 2m4m, 2m6m, 4m6m, 2m4m6m with the target found in every available plane), Post Hoc: Target eccentricity, Number of planes, Target clutter	Clutter levels (Low, High), Target clutter (Low, High), Target Z (Near, Far), Target Location (Center, Edge),
Task	Visual search task	Visual search task	Visual search task

Experimental Design	$n = 12$ 3x3x2 5 replications AR UI Clutter Level (3) – within AR Object % (3) – within Target Type (2) – within	$n = 12$ 2x12 5 replications AR UI Clutter Level (2) – within AR UI Configuration (2) – within	$n = 12$ 2x2x2x2 5 replications AR UI Clutter Level (2) – within Target Clutter (2) – within Target Z (2) – within Target Location (2) – within

1.3 Contribution

The speed of augmented reality development and adoption has outpaced knowledge of AR user interface design and evaluation, while AR use cases are expanding to include such diverse fields as commercial diving, entertainment, medical, military, warehousing, and manufacturing [3], [5]–[9]. The purpose of this work is to better characterize the effects of visual clutter on visual search time in AR UIs as well as the effects of other AR UI element properties such as target clutter, target eccentricity, target apparent depth, target type (projected or virtual), percentage of AR objects in an UI, and number of apparent AR UI planes. These will be used to make the following contributions to the field of augmented reality:

1. Empirical data on the use of extant image analysis measures of clutter
2. Empirical data on the relationship between visual clutter and visual search time in augmented reality
3. Empirical data on the effects of apparent AR UI depths on visual search time
4. Empirical data on the effects of other AR UI properties on visual search time to include:
    a. Target Type (projected or AR)
    b. Ratio of AR to projected objects in an AR UI
    c. Number and arrangement of AR UI planes
    d. Target Clutter
    e. Target eccentricity, target apparent depth, and target total apparent distance
5. An algorithmic relationship between an adjusted interface image analysis score of clutter, and visual search time. (i.e. User Interface 1 has a higher score than User Interface 2, therefore users are predicted to have a longer visual search time with Interface 1)

2 Background

2.1 Definitions

2.1.1 Augmented Reality

2.1.1.1 What is augmented reality?

The term augmented reality (AR) describes systems that blend computer generated virtual objects or environments with real environments [10]–[12]. Augmented reality adds extra visual information to the real world and as a display type, AR falls on the reality – virtuality continuum as first developed by Milgram to include; “tangible user interfaces, augmented reality (AR), augmented virtuality (AV) and virtual reality (VR)” [13]. Milgram then expanded this into more detail by separating (AR) into the categories of “spatial AR” and “see-through AR”, and separating (VR) into the categories of “semi-immersive VR” and “immersive VR” [13].

This reality-virtuality continuum was further revised by [14] to better represent advancements in technology as well as the idea that it is not a pure continuum as there is a disconnect between “external virtual environments” and “matrix-like virtual environments”.

In a multi-sensory real environment, the user only experiences real-world phenomenon, while in pure virtual reality, the user only experiences virtual phenomenon. Mixed reality is any combination of both real-world phenomenon and virtual phenomenon, while augmented reality is the addition of virtual phenomenon to the real world. Augmented reality can be further subdivided into a few main types depending on the hardware used and resulting user experience; composite video, handheld AR, heads-up display AR, and optical see-through head-worn AR.

2.1.1.2 Types of augmented reality

2.1.1.2.1 Composite video augmented reality

One of the most well-known and widespread examples of augmented reality is the “1st and 10” system used in football games, which adds a digital 1st down line onto the field that is seen on broadcasted football games. The “1st and 10” system was started in 1998 and has found continued success because users fount that the AR system provides non-distracting and value added information [15]. In contrast with the success of the “1st and 10” system is the FoxTrax hockey puck tracking system, better known as “Glow Puck”. This system added graphics highlighting the hockey puck and creating a tail for the hockey puck based on the speed at which the puck was moving. Users considered the system distracting, and juvenile, and it only lasted two years, from 1996 to 1998. [16].

As these two examples demonstrate, augmented reality can provide useful information that is valuable to the user in a non-distracting way, or it can provide unneeded, unwanted, and distracting information that does not provide value to the user.

2.1.1.2.2 Handheld augmented reality

Similarly, to the above examples of visual information added to a video broadcast, augmented reality can also include information added to a handheld system, with the most widespread handheld system being modern cell phones. Examples of handheld AR include the game “Pokémon Go” and the Ikea “Place” app [17], [18], since both applications use AR, to add extra virtual objects to the real world.

2.1.1.2.3 Head-up display augmented reality

Augmented reality is also found in the automotive and aviation industry, commonly with virtual objects being projected onto the windshields or presented via an optical combiner mounted low on the dash or high in the sun visor position. An automotive example of this type of AR was first seen on a 1988 Oldsmobile Cutlass Supreme [20]. This rudimentary AR only showed the current vehicle speed and turn signal activation. A newer example of this type of AR found in some BMW models

[19], [20], now shows navigational directions, collision and lane departure warnings, as well as speed limits and current vehicle speed.

2.1.1.2.4 Head-worn optical see-through augmented reality

Increasing computational ability in smaller devices has given rise to the proliferation of head worn AR UIs. These AR devices range in fidelity and immersion from a 2-dimensional display of data as seen in Oakley AR ski googles [22], to a fully immersive and interactive 3-dimensional virtual objects as seen in a virtual cadaver using the HoloLens [21], [22].

This research will focus on the optical see-through AR UI devices since these devices can and have been applied to many domains since the devices only requires the user to wear goggles or glasses, and, can be added to existing safety equipment such as protective goggles, helmets, and hardhats. Proof of the diverse range of domains in which see-through AR UIs is seen in the variety of their current domains and applications; commercial diving [5], medical [7], and assembly [11].

2.1.1.3 Accommodation and vergence in augmented reality

Stereo head-worn see-through optical AR displays can have issues with vergence-accommodation conflict. This is a conflict between accommodation, the mechanism by which the eye changes focus from distant to near images [23] and vergence, the simultaneous movement of both eyes in opposite directions to obtain or maintain single binocular vision [24]. This conflict occurs in stereo head-worn see-through optical AR when the eyes converge on a virtual object that is presented at a different apparent distance than the fixed focal plane(s) used by the AR optics. Two spatially offset views are provided to the left and right eyes, but the eyes' lenses accommodate at the depth(s) of the display [25]. The human visual system has the ability to tolerate this mismatch to some degree, but depth perception can be distorted and may effect some users more than others [26]. Varifocal displays [27]are an emerging solution to the vergence-accommodation mismatch in optical see-through AR, which is expected to provide more naturalistic viewing of combined virtual and real-world referents at matched distances.

2.1.2 Visual Clutter

Visual clutter is an issue that most are familiar with, from trying to find keys in the morning in a cluttered house, to finding an important memo on a cluttered desk, and even deciding what to order from a cluttered menu at a restaurant. The world is full of objects, and the visual clutter caused by these objects can negatively affect one's ability to find a given visual object of interest [28]. Augmented reality user interfaces add another layer of visual information to our world, which can assist in completing different tasks, but these extra visual objects inherently add more visual stimuli and potentially clutter. This additional clutter could then negatively affect user performance and usability. Establishing a better understanding of visual clutter in AR displays will help to limit the negative effects of visual clutter and encourage the adoption of this new and helpful display technology.

2.2 Related Work

2.2.1 Defining Visual Clutter

There are many informal definitions of what constitutes visual clutter, but for the purpose of research, visual clutter needs to be clearly defined. Previous research into visual clutter have defined it in several different ways:

> *"The level of visual clutter in a display or scene is related to the ease of adding an attention-drawing target to that display or scene."* [29]

> *"Clutter may obscure other problems during decision making processes while observing data."* [30]

> *"Additional visual stimuli, or clutter, on the AR display may increase the difficulty of successfully completing a visual search task on the primary display, and, a high density of information on the primary display may make it difficult to detect and comprehend information presented on the AR display."* [31]

> *"The state in which excess items or their representations or organization, lead to a degradation of performance at some task."* [32]

> *"Clutter can be thought of as a subjective impression of "visual chaos"."* [33]

> *"Too much data on too small an area of the display will result in visual clutter, which in turn diminishes the potential usefulness of the visualization."* [34] *"Visual clutter is defined as any aspect of the visualization that interferes with the viewer's understanding of the data."* [35]

> *"Visual clutter can be defined as the situation in which a determine number of objects, features or items as well as their organization prevent a person's ability to easily detect or recognize what is occurring in the scene, and, the level of visual clutter is analogous to the difficulty for a person to notice a note based on its location or appearance on a highly cluttered desk."* [36]

These definitions of visual clutter can be separated into two different approaches, visual clutter defined by what it does to the scene, and visual clutter defined by how it affects the user. Following is a summary table of these two different approaches found throughout the literature.

Table 2. Defining Clutter

Visual Clutter Defined by What It Does	
Visual Clutter obscures relevant information	[25], [35], [37]–[42]
Visual Clutter creates a chaos	[33]
Visual Clutter presents unneeded information	[38], [43]–[47]
Visual Clutter presents redundant information	[43], [48]–[50]
Visual Clutter Defined by the Effects it has on Users	
Visual Clutter is the ease or difficulty in the ability to add an object to a scene that a user will notice	[29]
Visual clutter is how easy or hard it is to notice any given object in a scene	[36]

Visual clutter is anything that degrades performance	[32], [34]

2.2.2 Effects of Visual Clutter

2.2.2.1 Visual search time

Visual clutter shows a strong correlation to visual search time across several different studies. In a general search task, [51] showed that visual search time increased as a function of visual clutter, where visual clutter was measured using image processing techniques (sub-band entropy, feature congestion, and edge density). In a search task using overhead views of different city types (rural, urban, and suburban), [52] found that visual search time increased with increased clutter, where clutter was measured with subjective ratings and image processing techniques (edge density and feature congestion). In a search task involving medical records on a screen, [53] found an increase in visual search time (defined as screen gaze time) from a low clutter condition mean gaze time of 20.05 sec to a high clutter condition mean gaze time of 26.38 sec, where clutter is measured by the amount of extra information on the screen, with low and high clutter conditions having the same amount of relevant information. In a map based search task, [54] found a linear relationship between the visual search time and clutter where clutter was measured by set size. [45] explored a target detection task, and found a 25% increase in target identification time between low and high levels of visual clutter, where clutter was measured as the amount and saliency of the objects on the display. [55] found that mean visual search time increased by a statistically significant difference of 23.3 seconds between scenes rated subjectively as high cluttered as opposed to low cluttered.

2.2.2.2 Mental workload

Increasing visual clutter leads to increases in perceived workloads as shown in several domains and experiments. [56] showed that air traffic controllers who rated displays as more cluttered also rated their workload higher, based on a NASA-TLX survey. This correlation between higher clutter and higher workload was also found by [57] and [37]. Increased visual clutter has also been theorized to lead to an increase in memory load by [58] who used a task where participants had to remember a route through a city. The researchers varied the level of extraneous information in each route as a stand in for clutter levels. Route patterns were described equally accurate between clutter levels, but higher clutter levels resulted in more incorrect landmarks, suggesting that irrelevant visual detail caused extra memory loading, resulting in more errors on secondary information (landmarks). It seems that complex visual environments may be problematic, causing disorientation and extraneous processing overload [59].

2.2.2.3 Increased errors

Increased visual clutter also leads to increased rates of errors. [60] showed the correlation between visual clutter and error rates in a military target identifying task, [61] in a flight gauge monitoring task, and [55] in a "where's waldo?" search task. [62] using set size as a measure of visual clutter, found that as set size increases, so do error rates. While [54] found that increased clutter leads to increased error rates; they determined that this only held true for divided attention tasks. When a task required an individual to focus attention in one area, clutter levels did not seem to affect error rates. [53] summarized that increased clutter leads to increased error rates. These studies show that there is a strong correlation between errors rates and visual clutter. Compounding the effects of increased error rates is that not only does clutter cause increased errors, it also significantly increases users confidence in their decision on erroneous trials [63].

2.2.2.4 Summary of research findings of effects

Table 3. Summary of Clutter effects

Effect	
Increased Visual Search Time	[45], [51]–[55]
Increased Mental workload	[37], [56]–[59]
Increased Errors	[37], [53]–[55], [60]–[62]
Increased Confidence in Erroneous Responses	[63]

2.2.3 Measures of Visual Clutter

Visual clutter is a complex issue with a variety of negative effects on user performance. In order to understand and potentially mitigate these negative effects, it would be valuable to be able to measure or even predict visual clutter. Many different measurements of visual clutter have been developed, each with their own purpose. The complexity of visual clutter along with the uniqueness of AR UIs in comparison to tradition UIs necessitate using a variety of different types of measures such as objective performance measures, image processing techniques, subjective ratings of clutter and mental workload ratings in order to more completely characterize visual clutter issues and effects on user performance.

2.2.3.1 Visual search time

Visual clutter correlates with visual search time and visual search time reflects both the usability of an interface, and is an established proxy measurement of cognitive load of a user interfaces [31],[54]. When applied to information visualization, it is a measure of how effectively information is displayed in terms of noise and saliency [64]–[66]. Visual search time represents the effectiveness of a display in terms of a single number, making it a useful measure for comparing different user interfaces. As a single number though it does not offer granularity into the perceived experience of the user. It also does not capture error rate, and is reliant on participant memory and confirmation bias.[67], [68]

Visual search time reliably correlates with clutter, increasing as clutter increases [52], [53], [69], with this correlation holding true across several domains and conditions. These domains and conditions include; a ship navigation task [70], a map search task [54], an intruder identifying task on a naval ship [45], a general search task [55], flight tasks [71], and a driving task using a night vision system [72].

In addition to the established correlation between visual search time and clutter, visual search time has been use to quantify human visual search performance [73]–[82]. Visual search time has also been used for comparing and quantifying user interfaces in aviation [83], virtual reality (VR) [84], AR UIs in a driving task [85]–[88], AR UIs for a medical task [89], and AR UIs with different spatial properties [90]. If visual search time is expanded to include job completion time, it has seen use as a metric to analyze AR UIs in warehouse “order picking task” [8], [91].

2.2.3.2 Error rates

Error Rates are considered an important measure of visual clutter since reducing errors is given high priority in many real-world tasks. Several researchers have shown a strong correlation between increasing levels of visual clutter and error rates; [55], [92], [93]. As clutter increases we also see an increase in subject's confidence in their answers whether right or wrong [63].

Visual clutter also leads to increased errors in the specific case of target detection. The probability of detecting a target decreases in high clutter environments as opposed to low clutter environments [60], and accuracy and false alarm errors increases as a display becomes more cluttered [54], [62]. These target detection errors were most severe in divided attention tasks, but still present focused attention tasks.

2.2.3.3 Set size

Set size is a way of measuring the visual information density of a user interface using the idea that the more objects in the interface, the more information, and therefore the longer it will take to complete a visual search task [78], [94], [95]. Set size is analogous to clutter and is used as a standin for visual clutter. As set size increases, the scene becomes more cluttered. While set size can be used as a good measure of clutter for simple displays, it runs into difficulty in more complex and more naturalistic displays. Particularly when dealing with complex objects it is difficult to discern if the object should be considered as a single object in the "set" or as multiple objects [29], [96].

Because of this, when analyzing more complex and naturalistic displays, other measures such as Feature Congestion, and Sub-band Entropy are more appropriate.

2.2.3.4 Feature congestion

An independent measure of visual clutter based on the characteristics of an image is feature congestion [97]. Feature congestion represents the amount of clutter in a scene by providing a single number based on a weighted measure of color, luminance contrast and orientation within a scene. Feature congestion serves as an algorithmic summary of the difficulty in drawing attention to an object added to a scene. As the amount of objects in a scene increases, it becomes more difficult for users to identify and find objects [98]. Feature congestion scores give an independent rating for clutter that each new object adds to a scene and gives insight into the difficulty of finding an object that has been added to an existing scene. It has been shown to correlate to visual search time [52], [97], [99], [100], as well as correlating with other methods of measuring visual clutter, such as background object density [101], object clutter [96], and sub-band entropy [99], [100].

2.2.3.5 Sub-band entropy

The principle of sub-band entropy is that visual clutter in a scene correlates to how efficiently a computer can encode an image while maintaining perceptual image quality [99], [100]. Sub-band entropy positively correlates with visual search time, and also with other measures of clutter such as background object density [101], object clutter [96], and Feature Congestion [99], [100]. An important limitation of sub-band entropy in the evaluation of UIs is that the encoding calculation fails to capture the effects of color on clutter. As such, it is commonly used in conjunction with an image analysis technique that does account for clutter, in this study, that is feature congestion.

2.2.3.6 Edge density

Clutter may also be measured using an algorithmic analysis of the number of distinct edges in an image. The number of edge pixels are then calculated and taken as a percentage of the total amount of pixels in an image, or the density of edge pixels. The principle behind this process is the idea that more edges relate to more distinct visual objects and therefore more clutter. This form of image processing is also theorized to be similar to how humans mentally process an image [102]. Edge density was first proposed as measure of the complexity of an image by [103], and later was found to correlate with visual search times. This correlation was reaffirmed in several experiments and search task contexts including a map search task [99], [100], pedestrian detection task [72], and rating real world scenes [52], [69].

2.2.3.7 NASA-TLX

Increasing the amount of visual clutter and therefore information in a system increases the mental workload of the participant [37], [43], [45]. This increase in mental workload can lead to a decrease in both situational awareness and the ability to find and encode objects in a visual search task [104]. It has also been shown that an increase in visual clutter can instill confidence in wrong judgments [63]. Therefore, we need to measure how a participant perceives the workload of different environments. An established subjective measure of mental workload is the NASA-TLX, which provides and overall rating of subjective workload based off of six dimensions; mental demand, physical demand, temporal demand, performance, effort, and frustration [105].

The NASA-TLX shows applicability across domains and has demonstrated robustness in research [106]. The correlation between NASA-TLX workload scores and clutter levels has been shown several times; [42], [43], [46], [55], [57], [58], [107], [108].

2.2.3.8 Summary of measures

In summary, there are three different measurement approaches for characterizing visual clutter: objective measures, image processing techniques, and subjective measures. Each of these measure types has its own benefits and drawbacks, as well as experimental applicability.

Table 4. Summary of Measurements

Measurement Type	**Measurement**
Objective Measures	Visual Search Time
	Accuracy and Error Rates
Subjective Measures	NASA-TLX
Image Analysis Measures	Set Size
	Feature Congestion
	Sub-band Entropy
	Edge Density

2.2.4 Visual Target Eccentricity

2.2.4.1 Effects of visual eccentricity on visual search time

Eccentricity in visual search is relationship that as the angle that light enters the eye increases, visual search time also increases [109] and has been shown by [109]–[114]. It has also been shown that it correlates with visual processing speed as well [115]. The effect of eccentricity is not limited to periphery and central focus, but shows differences of visual angles of eccentricity between 2° and 11° [109]–[115].

2.2.4.2 Visual eccentricity and visual clutter

Eccentricity has shown to have interaction effects with different methods of quantifying visual clutter in visual search tasks and visual processing as well as visual search time. In a map reading task, eccentricity was shown to interact with feature congestion measures of the clutter of a map for the metric of visual processing [116]. A non-linear interaction between visual search time, and measures of eccentricity and feature congestions was found by [117]. Their study showed that the effects of increasing eccentricity were less severe for images with low feature congestion (clutter), than for images with high feature congestion. Eccentricity has also shown to have an nonlinear interaction with set size in visual search tasks [110]. With there being a less of an effect of set size for targets at smaller angles of visual eccentricity at 2.2° than 4.7° [118], 3.5° [119] than 5° [120].

2.2.4.3 Visual eccentricity in augmented reality

One of the main differences of AR displays versus traditional displays is that an AR display has the ability of putting information at varying depths from the user. This is important as eccentricity has shown to have interaction effects with target depth when using a physical realworld display [121] with visual search time being shorter for far targets vs near targets for low eccentricity 2.8°, but with visual search time being longer for far targets (+2.46cm from fixation plane) vs near targets (-2.46cm from fixation plane) of medium (4.8°) or high (7.1°) eccentricity. This significant interaction between eccentricity and target depth was also found by [9] when using a multi-layered LCD display of two screens.

2.3 Measures Used in Studies

Visual clutter is being used as a measure for interface effectiveness as clutter may obscure relevant information [25], [35], [37]–[42], present unneeded information [38], [43]–[47], and present redundant information [43], [48], [50], [122]. Visual clutter also increases the difficulty of finding an object added to a scene [100] as well as making it harder to notice any one given object of a scene [36].

Visual search time was selected over NASA-TLX as this work is focused on establishing a relationship between AR UI features and users' visual search performance, and not on user perceptions of the AR UI, as the focus of this research is on occupational instead of consumer use of AR UIs. Eye tracking was also considered as a measure, but that level data granularity on search patterns was not thought necessary during this phase of establishing a general relationship between AR UI features and performance. Error rates and accuracy were not recorded as participants were encouraged to try to find objects as quickly as possible to establish the upper bound of performance when errors or accuracy were not a focus.

3 Commonalities Across All Studies

The following studies share many general similarities in equipment, setup, measures and limitations which will be detailed here.

3.1 Equipment

3.1.1 Equipment used across all studies

The experimental test bed was developed in Unity3d (version 2019.1.8f1). 3D objects were processed with Maya and Microsoft 3d Viewer. AR objects were presented via a Microsoft HoloLens1 device. The HoloLens1 has a holographic resolution of 2.3M total light points, a holographic density of over 2.5k radiants (light points per radian), refresh rate of 240Hz (60Hz content rate, each frame consists of four sequential colors: R-G-B-G), and a field of view of 30°H and 17.5°V. The optical distance of the HoloLens1 is fixed at approximately two meters [66]. The HoloLens1 application was embedded with visual search time tracking code and used Vuforia image recognition software to initially orient the AR UIs. User input to the HoloLens1 was through a Logitech K380 multidevice Bluetooth keyboard.

3.1.2 Equipment specific to Study 1

Projected objects were displayed using Microsoft PowerPoint as the display software and a laptop connected to an Epson Powerlite Pro G6900WU projector as the display hardware. The Epson

Powerlite Pro G6900WU projector has a native resolution of WUXGA (1920 x 1200) resized to 0.63m x 1.15m, to match the size of the field of view of a HoloLens at two meters. Images were projected onto a sheet of white paper which was hung on a wall.

3.2 Clutter Levels and AR UI Generation

3.2.1 Image Analysis Settings

Sub-band entropy and feature congestion were analyzed using the provided Matlab code from [100], [123]. Measures of sub-band entropy and feature congestion were taken for the target object and for a 2D images of the projected object array, the AR object array and the combined object array.

Edge density was measured using the Canny Edge Detection algorithm provided in the MATLAB image processing toolbox [62]. The Canny Algorithm uses a low threshold variable, a high threshold variable, and a sigma parameter which is the standard deviation of the Gaussian filter used in the computation of the gradient, as in [61] these were set to 0.11, 0.27. and 1, respectively. Measures of edge density were taken for the target object, and 2D images of the projected object array, the AR object array and the combined object array.

3.2.2 Objects

In pursuit of keeping the visual search task domain independent while still being naturalistic and familiar to participants, a selection of everyday household objects was chosen as the set of objects for the visual search task. Objects come from a 3D scan of an entire room and its contents of an individual's house. The scan of the room was in the mayaBinary (.mb) format. Objects were separated from the set by exporting individual objects from Maya into the FILMBOX (.fbx) format, the FILMBOX format was chosen as this format can be directly imported into Unity3D, as well as viewed with Microsoft's 3D viewer. The objects, now in (.fbx) were rotated so that what would be considered the "front", or the "face" of the object was facing the user and were size corrected to fit within a .1x.1x.1m cube.

The front "face" of the object was then exported as a Portable Network Graphic (.png) file, with transparency and at a resolution of 1280 x 1024. After this, the PNG file of the object was opened in Microsoft paint and manually resized and scaled to minimize negative space and to bring the resolution to 1000 x 1000.

Clutter measures (feature congestion, sub-band entropy, and edge density) were taken for the face of each object as follows. Objects were opened in Microsoft 3D viewer, checked to ensure that they were oriented so only the "front" of the object was visible and the lighting was set as follows; lights 1, 2, and 3 were set to off, the environment lights were set to Intensity=200, Value=100, Hue=0, Saturation=0, and Shadows=Off. The face was then saved as a 2D png. file. This is necessary because the image analysis clutter measures can only analyze 2D images. The image analysis measures were then normalized and summed to give an overall clutter value for each object.

3.2.3 Creating AR UIs

Each AR UI was comprised of 36 objects placed into one of 45 positions on a 9x5 grid, where each grid square had a visual angle of 2.8642° wide by 2.8642° tall as seen in Fig. 1. (This is equivalent to a 0.1m x 0.1m square when viewed at a distance of 2m). The number of objects for each AR UI Clutter Level (low, medium, and high for study 1) and (low and high for studies 2 and 3) was kept constant to mitigate effects of set size on the visual search task [124].

1	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**
10	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**18**
19	**20**	**21**	**22**	**23**	**24**	**25**	**26**	**27**
28	**29**	**30**	**31**	**32**	**33**	**34**	**35**	**36**
37	**38**	**39**	**40**	**41**	**42**	**43**	**44**	**45**

Fig. 1. Grid with numerical position map, position 23 was centered in the field of view for each subject.

Objects were ranked from least cluttered to most cluttered by taking the average of the normalized values of edge density, sub-band entropy, and feature congestion. AR UIs were then created by arranging sets of 36 objects on a 9x5 grid.

3.2.3.1 Study 1

Objects ranked 1-36 were used to make low clutter AR UIs, 6-41 for medium clutter AR UIs, and 10-45 for high clutter AR UIs. Due to a limited availability of objects low and medium AR UIs shared 31 objects, medium and high AR UIs shared 32 objects and low and high arrays shared 27 objects.
AR UIs were created using code based on Excel's RNG function to assign an object to a grid position and depth for each trial. Code based on Excel's RNG function was then used to select which object would be the target object.

For the image analysis measures, VBA code was used to map PNGs of the "front" of each 3D object to their AR UI positions. These AR UIs were saved (without compression) as PNG files. PNG files of AR UIs were then analyzed to check for within clutter level consistency, i.e., all low clutter AR UIs should have similar image analysis results. The results of this analysis can be seen in the sections for Study 1.

3.2.3.2 Studies 2 and 3

Objects ranked 1-36 were used to make low clutter AR UIs and objects ranked 10-45 for high clutter AR UIs. Due to a limited availability of objects, both high and low AR UIs shared 27 objects. Previous research [125], [126] indicated that despite the overlap, there is enough of a difference to have a discernible effect on visual search times. AR UIs were created using code based on Excel's RNG function to assign an object to a grid position and depth for each trial. Code based on Excel's RNG function was then used to select which object would be the target object.

AR UIs were generated with coding to ensure there was no object occlusion. When objects in the AR UI were presented at distances other than 2m, objects were scaled within the Unity program to maintain each objects apparent size at a consistent visual angle of 2.8642° to avoid issues of apparent size of the object affecting visual search time.

In study 2, 2D representations of the objects were used to create the AR UIs while in Study 3, 3D objects were used to create the AR UIs

For the image analysis measures, VBA code was used to map PNGs of the "front face" of each 3D object to their AR UI positions. These AR UIs were saved (without compression) as PNG files. PNG files of AR UIs were then analyzed to check for within clutter level consistency, i.e., all low clutter AR UIs should have similar image analysis results. The results of this analysis can be seen in the section for Study 2 and Study 3.

3.3 Measures

3.3.1 Visual Search Time

Participant performance was measured using visual search time. Visual search time was calculated as the time between the participant pressing the "space key" which indicated that they were ready for the visual search task, and which displayed the AR UI, and the participant pressing either the "J" or the "F" key, which indicated that they had found the target. Time was recorded via the HoloLens1 application. Target identification was self-reported and independent measures of accuracy were not taken. If a participant indicated that they had selected the wrong object or had erred in any other way, that trial was marked as incomplete, and the data was not included in the analysis.

3.3.2 Visual Target Eccentricity

The eccentricity of targets was measured as the angle of the target from the center of the AR UI, which was centered with the users' field of view. Eccentricity was calculated using the coordinates of the target on the AR UI "grid" (See Section 3.2.3) and the apparent distance from the user. The size of the grid was based on a constant visual angle so the grid size increased as the distance from the user increased. This means that the target eccentricity for a target in "grid position 1" would be the same for the grid at any apparent distance from the user. Visual angle was kept constant so the apparent size of the objects would be constant, and visual search time would not be a function of object size. The measurements for calculating eccentricity used the center of the grid square, with "$grid\ position\ 1 = (0,0)$". Using this method, the eccentricity was calculated in degrees of visual angle. The eccentricity was further divided into the horizontal component of eccentricity (horizontal visual angle), the vertical component of eccentricity (vertical visual angle) for analysis as well. Results of the positions are shown in the following figure.

(11.31°, 5.71°) 12.6°	(8.53°, 5.71°) 10.22°	(5.71°, 5.71°) 8.05°	(2.86°, 5.71°) 6.38°	(0°, 5.71°) 5.71°	(2.86°, 5.71°) 6.38°	(5.71°, 5.71°) 8.05°	(8.53°, 5.71°) 10.22°	(11.31°, 5.71°) 12.6°
(11.31°, 2.86°) 11.65°	(8.53°, 2.86°) 8.98°	(5.71°, 2.86°) 6.38°	(2.86°, 2.86°) 4.04°	(0°, 2.86°) 2.86°	(2.86°, 2.86°) 4.04°	(5.71°, 2.86°) 6.38°	(8.53°, 2.86°) 8.98°	(11.31°, 2.86°) 11.65°
(11.31°, 0°) 11.31°	(8.53°, 0°) 8.53°	(5.71°, 0°) 5.71°	(2.86°, 0°) 2.86°	(0°, 0°) 0°	(2.86°, 0°) 2.86°	(5.71°, 0°) 5.71°	(8.53°, 0°) 8.53°	(11.31°, 0°) 11.31°
(11.31°, 2.86°) 11.65°	(8.53°, 2.86°) 8.98°	(5.71°, 2.86°) 6.38°	(2.86°, 2.86°) 4.04°	(0°, 2.86°) 2.86°	(2.86°, 2.86°) 4.04°	(5.71°, 2.86°) 6.38°	(8.53°, 2.86°) 8.98°	(11.31°, 2.86°) 11.65°
(11.31°, 5.71°) 12.6°	(8.53°, 5.71°) 10.22°	(5.71°, 5.71°) 8.05°	(2.86°, 5.71°) 6.38°	(0°, 5.71°) 5.71°	(2.86°, 5.71°) 6.38°	(5.71°, 5.71°) 8.05°	(8.53°, 5.71°) 10.22°	(11.31°, 5.71°) 12.6°

Fig. 2. Angles of eccentricity for different target locations.

3.4 Limitations

Limitations of this study were a limited range of objects to search for, and a lack of fidelity to real world visual search tasks because of the use of a semi structured search task using household objects. The representation of the AR UI is in a grid format, which may not be applicable to other types of AR UI layouts. Another limitation is that the projected objects were 2D representations of real objects displayed via a projector instead of being physical objects. A large limitation was the limited field of view of the HoloLens1. As this study used head-mounted optical see-through AR with a world-fixed AR UI, it may not be applicable to non-head-mounted optical see-through ARs, different AR UI types or AR UIs that expand more into the periphery of the field of view. Different types of AR hardware and AR UIs may have different properties that affect visual search time, and the results of this study may not be applicable to other AR hardware and UI configurations. Another limitation is the focus of the studies on the upper bound of visual-search time and a lack of recording of accuracy or error measures, as for some tasks accuracy may be just as or more important that search speed.

The studies in this work are focused in the exploratory stage and have yet to be validated. As such, while this work may be currently applied to AR UIs, it will need to be checked for validity until validity has been better established.

4 Applying Measures of Visual Clutter to the Head Worn Augmented Reality Space

Abstract - This study examines the applicability of extant image analysis measures of visual clutter to optical see-through (OST) head mounted (HMD) augmented reality (AR) displays, in conjunction with other factors that may affect visual search time such as the percentage of AR objects compared to projected objects in an interface, and the type of object a user is searching for (projected or AR). Extant image analysis techniques of feature congestion, edge density, and sub-band entropy are specifically chosen to quantify clutter, as they can be applied to complex and naturalistic scenes, as is common to experience while using an AR UI. The end goal of this research is to develop an algorithm capable of predicting user performance through the metric of visual search time for a given AR UI. In this experiment, twelve participants performed a visual search task of locating a target object in an array of both projected and AR objects. Participants completed this task under three different clutter levels (low, medium, high) against three different levels of AR object percentage (25%, 50%, 75%) and two types of targets (projected, AR) with repetition. Results show significant differences in visual search time between clutter levels, AR object percentage, and target type. Participants consistently had more difficulty finding objects in more cluttered scenes, where clutter was determined through image analysis methods, and had more difficulty in finding objects when the AR of objects was at 50% as opposed to other conditions. Visual search time positively correlated to measures of combined clutter (AR and projected) arrays but not for measures of clutter taken of the individual array components (AR or projected).

4.1 Objective

Augmented reality (AR) is a rapidly growing technology that is seeing use in an increasing variety of domains and applications. The proliferation of AR means a steep increase in AR user interfaces (UI) and an urgent need for better methods of designing and evaluating these AR UIs, as well as understanding how AR UIs affect visual search time. The difficulty in accomplishing this, is that AR UIs are inherently different from traditional UIs, in that there are two sources of visual information simultaneously presented (projected and AR) in the same view field, and both sources of information may be need for a task. At a high level, AR users may at any time be interacting with one of three things: AR-only elements, real-world objects, and combined AR/real-world referents. Because of this complication, one cannot assume that extant measures of visual clutter will translate from traditional displays to AR UIs.

Clutter is detrimental to the performance of any interface. It leads to errors, and increased time in finding objects of interest as well as increased time for decision making and increased mental workload. Addressing this is especially important for AR UIs as they are still a novel technology to most and adoption of this technology could be hindered by user interfaces that negatively affect performance. The inherent differences between AR UIs and non-AR UIs compounds this issue, as currently there are not tools that look at all aspects of an AR UI holistically and evaluate it as such.

This study focuses on applying extant image analysis techniques of measuring visual clutter since they are well suited for quantifying clutter in complex and naturalistic images that commonly occur in the real world. If these techniques prove applicable to the AR UI space, then they may be useful in examining each of the three sources of visual clutter (AR, projected, combined) and potentially to predict visual search time when using AR UIs. Other factors that may affect visual search time will be analyzed, such as the percentage of AR objects in a given AR UI, and whether a user is searching for a projected or AR object. A post-hoc examination of clutter inherent to a target object and target eccentricity was also done to identify possible variables of interest for future studies. Adjusting and validating extant image analysis techniques of measuring visual clutter in the AR UI space and exploring the effects of other factors on visual search time will allow the development of an algorithm that aims to analyze and compare different AR UIs to each other and rank them in order of expected user visual search time.

4.2 Method

4.2.1 Experimental Design

The study was designed as a multiple-factor, within-subjects experimental design. The study was fully crossed the independent variables of; "AR UI Clutter Level" (low, medium, and high), "AR Object Percentage" (25%, 50%, 75%), and "Target Type" (projected or AR). The final experimental design results in 18 conditions (3x3x2). The experiment was counterbalanced between “AR UI Clutter Level” and “Target Type”, while “AR Object Percentage” was randomized. The dependent variable was visual search time, and there were five trials at each condition, for a total of 90 trials per participant.

4.2.2 Participant Demographics

Institutional Review Board (IRB) approval was obtained, and twelve participants completed the study. The participants ranged in age from 20-26 years old with perfected or corrected vision. There were nine male and three female participants (men: mean age = 24, SD = 4.4; women: mean age = 22, SD = 2.5).

4.2.3 Equipment

Equipment used in this study is detailed in Section 3.1.

4.2.4 Clutter Levels and AR UI Generation

4.2.4.1 Image analysis settings

Settings for the extant image analysis measures of clutter are detailed in Section 3.2.1.

Projected objects were used as a stand-in for real world objects as it allowed all objects to be represented in 2D. This also allowed object sizes to be kept consistent between objects i.e., the “front face” of each object had to fit within a .1x.1m square and it allowed the object sizes to be kept consistent between representations of the objects as virtual or projected.

4.2.4.2 Objects

Object selection and processing is detailed in Section 3.2.2.

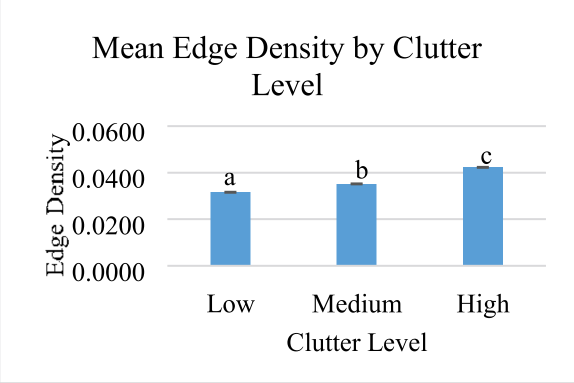
4.2.4.3 Creating AR UIs

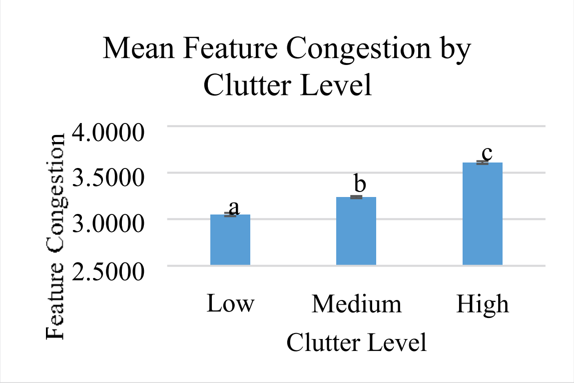
AR UI creation is detailed in Section 3.2.3.

The AR UIs were analyzed to check for within clutter level consistency, i.e., all low clutter AR UIs should have similar image analysis results. The results of this analysis are shown in the following table and figures.

Table 5. Image Analysis Details for Array Clutter Levels

		Edge Density	Feature Congestion	Sub-band Entropy
Array Clutter Low	Mean	.0316	3.051	2.894
	SD	.0002	.0176	.0160
Array Clutter Medium	Mean	.0352	3.238	3.059
	SD	.0002	.0114	.0108
Array Clutter High	Mean	.0423	3.609	3.135
	SD	.0002	.0147	.0176





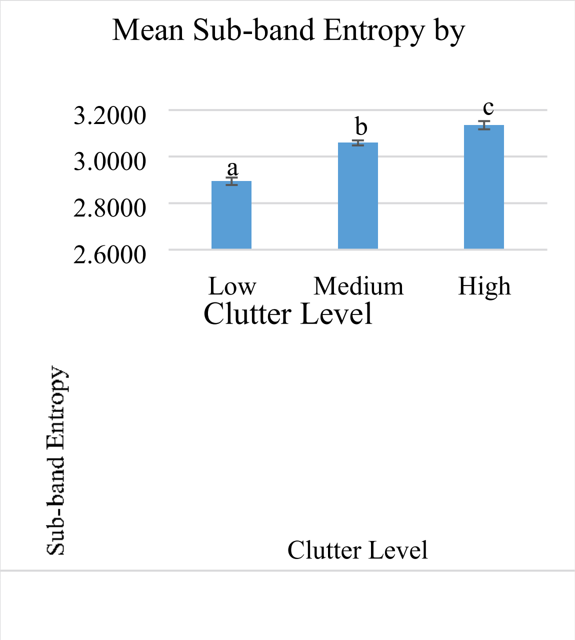


Fig. 3. Summary of different clutter metrics for low, medium, and high AR UI clutter levels

4.2.5 Visual Search Task and Procedure

Participants completed a series of visual search tasks by identifying a target object within an array of objects. The array of objects was comprised of randomized collection of household objects. To simulate visual search task that requires users to scan both projected and AR objects, the object arrays included both objects created with the projector (projected), and objects created with the HoloLens (AR). Image arrays were located two meters from the participant with AR and projected images being collocated on the same plane. Two meters was chosen as that is the fixed optical distance of the HoloLens to mitigate potential vergence-accommodation conflicts.

Participants were seated in a room with ambient light levels of 20 lux. They were given a Bluetooth keyboard, seated facing a neutral wall of off-white with a white posterboard the size of the viewing area mounted to the wall. They were then given the HoloLens1 to put on and instructed how to adjust the device so that it fit comfortably. To complete the task, participants were shown the object they had to find in the HoloLens, then, when ready to search for this object in the object array, participant hit the spacebar on a Bluetooth keyboard and were shown an AR UI comprised of objects which contained the target object (Fig. 11). Participants indicated that the target object was found by entering "f" or "j" (so that participants could use whichever hand they preferred) key on a Bluetooth keyboard (binary self-report). When the "f" or "j" key had been hit, the program recorded the time between the AR UI being shown, and the target being indicated as being located. The participant was seated at a desk and instructed to stay as still as possible, but not precluded from moving. This approach was done to put the participants view in line with the image used for the image analysis measures of the AR UI. Despite the instructions, slight movements could occur.

An example of what the user would see is shown in Fig. 4.

Fig. 4. Example of target array (medium clutter)

The participant was then given instructions on the task and completed 3-5 test trial searches. During these searches, it was also checked to make sure that the participant was seeing all objects correctly, i.e., objects along the edge were visible. Each participant experienced all combinations of three “AR UI Clutter Level” (low, medium, high), testing three different “AR Object Percentage” (25%, 50%, 75%), and searching for two different “Target Type” (projected, AR) for a total of 18 conditions where the target was found in every available combination of independent variables. Each combination of independent variables was known as a condition, there were 18 conditions, and 5 trials per condition for 90 trials/participant. Conditions were counterbalanced between “AR UI Clutter Level” and “Target Type”, while “AR Object Percentage” was randomized. Participants verbally indicated when they were ready for each new trial and took a short rest after the 30th and 60th trials.

Table 6. Summary of Experimental Conditions

Clutter Level	**Target Type**	**AR Object %**	**Condition**
Low Clutter	Projected Target	25%	1
		50%	2
		75%	3
	AR Target	25%	4
		50%	5
		75%	6
Medium Clutter	Projected Target	25%	7
		50%	8
		75%	9
	AR Target	25%	10

		50%	11
		75%	12
High Clutter	Projected Target	25%	13
		50%	14
		75%	15
	AR Target	25%	16
		50%	17
		75%	18

4.2.6 Measures

Participant performance was measured using visual search time. A detailed explanation of the collection of visual search time is found in Section 3.3.

4.3 Data Processing

Twelve participants each completed 5 trials of 18 conditions resulting in 1080 measurements taken. Of these 1080 data points, 2 were lost due to self-reported errors from the participants. Each condition (a combination of “AR UI Clutter Level”, “AR Object Percentage”, and “Target Type”) was then analyzed for outliers using the interquartile method. The interquartile range (IQR) for the data was determined then the IQR was multiplied by 1.5 (a constant used to discern outliers) and added to the third quartile, any number greater than this is a suspected outlier. This resulted in 55 outliers being identified out of 1080 measurements. After lost trials and outliers, there were 1023 remaining measurements. For the ANOVA, participant visual search times over the five trials per condition were averaged for the mean visual search time per condition per participant (18 data points/participant and 216 data points total). For the Pearson correlation, the average visual search time across all participants was taken for each trial of each condition (90 data points).

4.4 Analysis

Prior to analysis all conditions were checked for normality using the Shapiro-Wilks Normality test and an inspection of the Normal QQ Plot. Four out of 18 conditions; 4-(Array Low_50_AR Target), 5-(Array Low_75_Projected Target), 13-(Array High_25_Projected Target), and

16(Array High_50_AR Target) were found to be non-normal. Inspection of the QQ plot and the robustness of the repeated measures ANOVA did not necessitate a transformation. Performing a natural log transformation on the data did not result in any improvements of normality. Full results can be viewed in (Appendix 9.1). All statistics were conducted using IBM SPSS 26 and $\alpha=0.05$.

Two statistical modelling approaches were taken to analyze the model. First was a three-way repeated measures ANOVA of the independent variables of “AR UI Clutter Level”, “AR Object Percentage”, and “Target Type” on the dependent variable of visual search time. The second was using a Pearson correlation test to determine if continuous independent variables (clutter measures of the projected object array, the AR object array and the combined object array correlated with the dependent variable of visual search time. Post hoc analysis was done on the independent variables of target clutter level and target eccentricity.

4.5 Results

4.5.1 Three-way Repeated Measures ANOVA

A full factorial three-way repeated measures ANOVA was run on the independent variables of “AR UI Clutter Level”, “AR Object Percentage”, and “Target Type” and the dependent variable of visual search time. Tests of sphericity are shown in Table 7, followed by the results of the threeway repeated measures ANOVA in Table 8.

Table 7. Tests of sphericity

Within Subjects Effect					**Epsilon**		
Variable	**Mauchly's W**	**Chi-Square**	**df**	***p***	**Greenhouse-Geisser**	**Huynh-Feldt**	**Lower-bound**
AR UI Clutter Level	0.66	4.19	2	*p*=.123	0.74	0.83	0.50
AR Object %	0.55	6.05	2	***p*=.049**	0.69	0.75	0.50
Target Type	1.00	0.00	0		1.00	1.00	1.00
AR UI Clutter Level * AR Object %	0.07	25.68	9	***p*=.003**	0.47	0.56	0.25
AR UI Clutter Level * Target Type	0.38	9.60	2	***p*=.008**	0.62	0.66	0.50

AR Object % * Target Type	0.55	6.04	2	**_p_=.049**	0.69	0.75	0.50
AR UI Clutter Level* AR Object % * Target Type	0.32	10.64	9	_p_=.309	0.65	0.88	0.25

Table 8. Three-way ANOVA Results

Variable	**Analysis Type**	**Sum of Squares**	**df**	**F**	**_p_**	**_η_2**	**Power**
AR UI Clutter Level	Sphericity Assumed	4.44	2.00	55.01	**_p_ < .001**	0.83	1.00
	Greenhouse-Geisser	4.44	1.49	55.01	**_p_ < .001**	0.83	1.00
	Huynh-Feldt	4.44	1.67	55.01	**_p_ < .001**	0.83	1.00
	Lower-bound	4.44	1.00	55.01	**_p_ < .001**	0.83	1.00
AR Object %	Sphericity Assumed	2.52	2.00	34.74	**_p_ < .001**	0.76	1.00
	Greenhouse-Geisser	2.52	1.38	34.74	**_p_ < .001**	0.76	1.00
	Huynh-Feldt	2.52	1.51	34.74	**_p_ < .001**	0.76	1.00
	Lower-bound	2.52	1.00	34.74	**_p_ < .001**	0.76	1.00
Target Type	Sphericity Assumed	0.87	1.00	7.82	**_p_ =.017**	0.42	.72
	Greenhouse-Geisser	0.87	1.00	7.82	**_p_ =.017**	0.42	.72
	Huynh-Feldt	0.87	1.00	7.82	**_p_ =.017**	0.42	.72
	Lower-bound	0.87	1.00	7.82	**_p_ =.017**	0.42	.72
AR UI Clutter Level* AR Object %	Sphericity Assumed	2.27	4.00	16.42	**_p_ < .001**	0.60	1.00
	Greenhouse-Geisser	2.27	1.87	16.42	**_p_ < .001**	0.60	1.00
	Huynh-Feldt	2.27	2.24	16.42	**_p_ < .001**	0.60	1.00
	Lower-bound	2.27	1.00	16.42	**_p_ =.002**	0.60	.96
AR UI Clutter Level* Target Type	Sphericity Assumed	3.47	2.00	27.37	**_p_ < .001**	0.71	1.00
	Greenhouse-Geisser	3.47	1.24	27.37	**_p_ < .001**	0.71	1.00
	Huynh-Feldt	3.47	1.32	27.37	**_p_ < .001**	0.71	1.00
	Lower-bound	3.47	1.00	27.37	**_p_ < .001**	0.71	1.00
AR Object % * Target Type	Sphericity Assumed	3.12	2.00	46.48	**_p_ < .001**	0.81	1.00
	Greenhouse-Geisser	3.12	1.38	46.48	**_p_ < .001**	0.81	1.00
	Huynh-Feldt	3.12	1.51	46.48	**_p_ < .001**	0.81	1.00
	Lower-bound	3.12	1.00	46.48	**_p_ < .001**	0.81	1.00

AR UI Clutter Level * AR Object %* Target Type	Sphericity Assumed	0.40	4.00	4.23	***p* =.006**	0.28	.90
	Greenhouse-Geisser	0.40	2.62	4.23	***p* =.017**	0.28	.77
	Huynh-Feldt	0.40	3.51	4.23	***p* =.008**	0.28	.86
	Lower-bound	0.40	1.00	4.23	*p* =.064	0.28	.47

4.5.2 Pearson Correlation

A two-tailed Pearson correlation test was carried out between the mean of visual search time for each trial and individual image analysis measures of clutter (edge density, feature congestion, and sub-band entropy) for the combined AR UI, the array of projected objects, and the array of AR objects. A post-hoc power analysis was carried out using G*Power V3.1.9.7 [127] to test correlation using a two-tailed test an alpha of .05, the sample size of 90, and the calculated effect size. Results are summarized below.

Table 9. Pearson Correlation Summary

Variable	**r(df)**	***p***	**Power**
Combined Array ED	r(88)=.25	***p* = .017**	.61
Combined Array FC	r(88)=.27	***p* = .012**	.70
Combined Array SE	r(88)=.28	***p* = .008**	.75
Projected Array ED	r(88)=.06	*p* = .596	1.00
Projected Array FC	r(88)=.05	*p* = .674	1.00
Projected Array SE	r(88)=.02	*p* = .821	1.00
AR Array ED	r(88)=.11	*p* = .314	.52
AR Array FC	r(88)=.10	*p* = .354	.72
AR Array SE	r(88)=.06	*p* = .553	1.00

4.6 Discussion

4.6.1 Three-way Repeated Measures ANOVA

4.6.1.1 Main effects

In the full-factorial three-way repeated measures ANOVA a significant effect was found for the independent variables of "AR UI Clutter Level", "AR Object Percentage", and "Target Type". This result agrees with pervious work regarding the use of image analysis techniques as measures of clutter not in AR, [52], [69], [100]. It also agrees with other UI results of significance of clutter on visual search time [45], [52]–[55], [69]–[72].

The importance of this finding is not only that clutter affects visual search time in AR UIs, which would be expected by the literature, but also that the image analysis measures of clutter are viable candidates in the AR UI space and that AR UI clutter as a significant effect on visual search times.

The effect of clutter level on visual search time is important since many domains which see uses of AR have visual search time as an important metric, such as driving [126], aviation [128], and even warehouse operations [8], [91]. These results support the need for designing AR UIs of low clutter. The average visual search time for each clutter level is shown in Fig. 5.

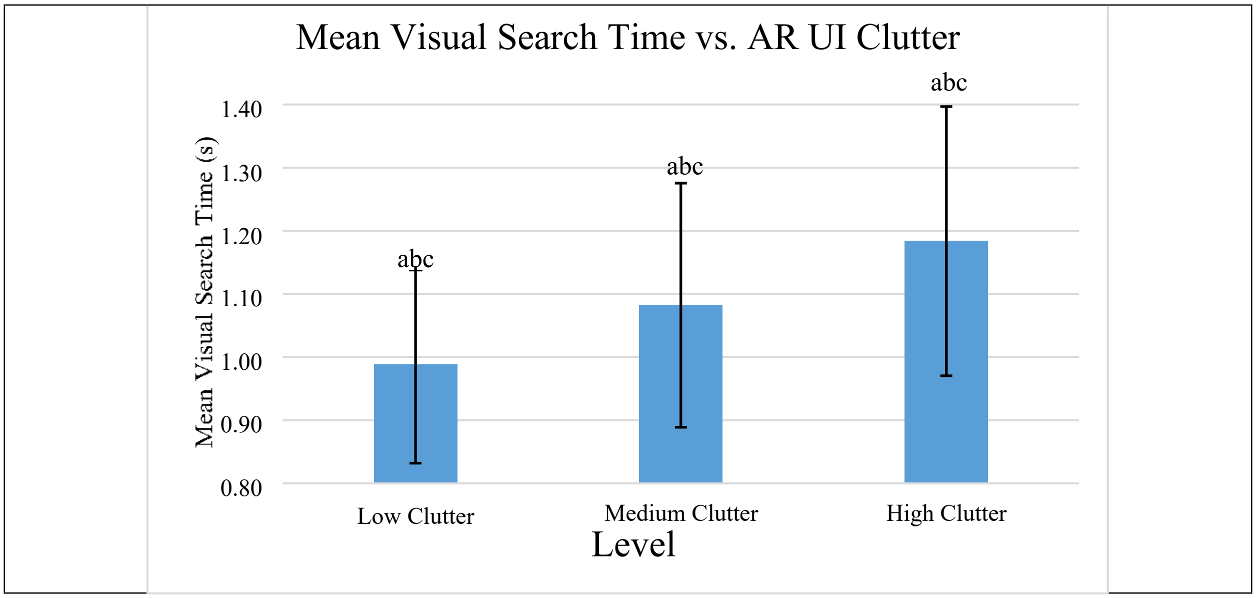


Fig. 5. Mean visual search time by “AR UI Clutter Level”, the ANOVA showed a significant effect of “AR UI Clutter Level” on visual search time.

The significant effect of “AR Object Percentage” on visual search time is important because it shows that the ratio of projected to AR objects has an effect on visual search time. The low and high “AR UI Clutter Level” conditions both had an increase in visual search time for the 50% AR object level, the medium clutter level did not show any trends. The 50% AR object condition would have the greatest amount of context switching between AR and projected objects. This decrease in visual search time as context switching increases agrees with previous findings [129], [130]. The differences in average visual search time based on “AR Object Percentage” and “AR UI Clutter Level” can be seen in Fig. 6.

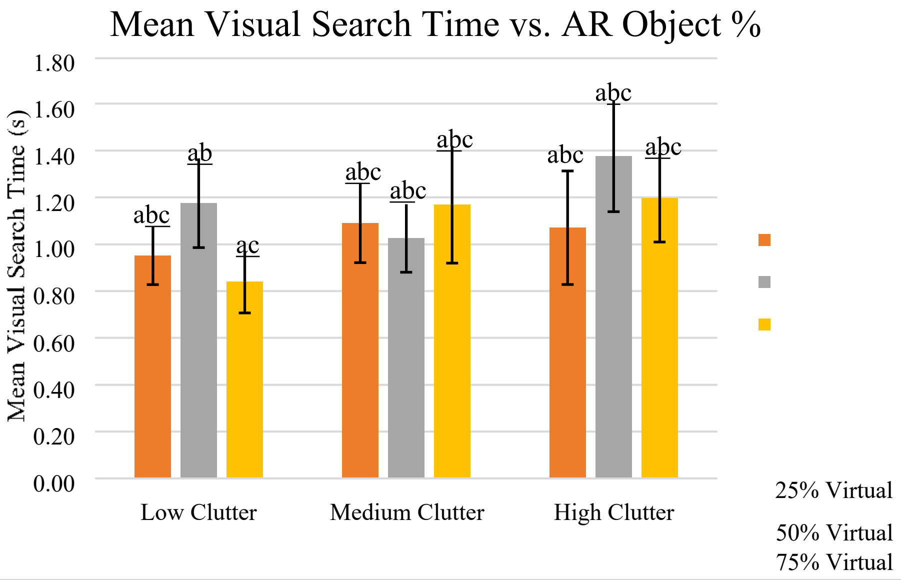


Fig. 6. Mean visual search time by “AR Object Percentage”. The ANOVA found a significant effect of “AR Object Percentage” on visual search time.

“Target Type” also had a significant effect on visual search time, with visual search time for projected targets being less than that for AR targets in the low and high clutter conditions. The medium clutter conditions did not follow this trend though. Reasons for this could be that AR objects might incur a higher processing time to recognize what the object is. Average visual search time based on “Target Type” and “AR UI Clutter Level” is shown in Fig. 7.

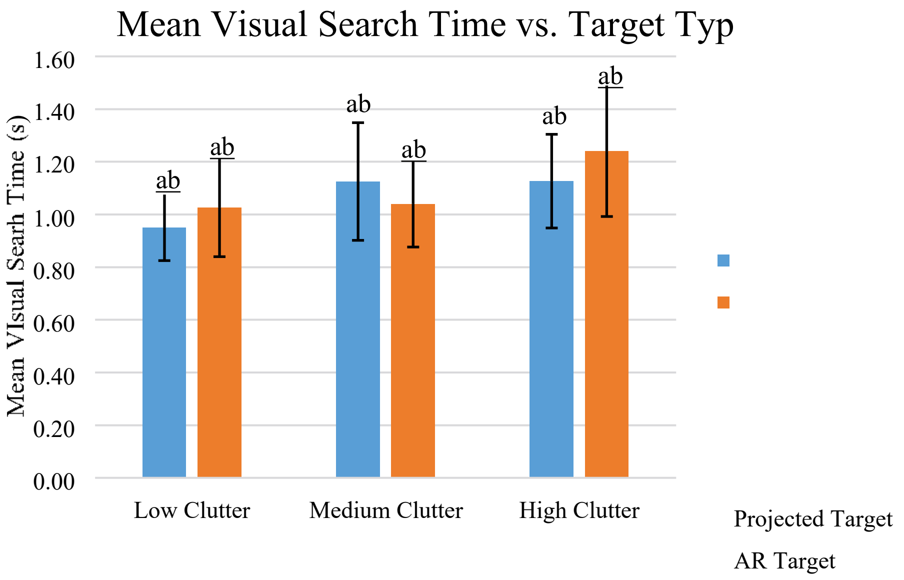


Fig. 7. Mean visual search time by “Target Type”. The ANOVA found a significant effect of “Target Type” on visual search time.

The medium clutter condition for both the variable of “Target Type” and “AR Object Percentage” did not follow the trend of the low clutter and high clutter conditions. This result could be caused by the medium clutter condition increasing attention and causing an unusual result, similar to [131]. It could also be due to a large amount of overlap in the image sets for each of the clutter conditions obscuring the results.

4.6.1.2 Interaction effects

A significant interaction effect was found between; (AR UI Clutter Level)*(AR Object %), (AR UI Clutter Level)*(Target Type), (AR Object %)*(Target Type), and (AR UI Clutter Level)*(AR Object %)*(Target Type).

For the significant interaction between “AR UI Clutter Level” and “AR Object Percentage”. In both the low and high clutter conditions, the 50% “AR Object Percentage” had the longest visual search times. The medium condition showed increasing visual search times with increasing "AR Object Percentage". A reason for this could be the issues of increased context switching as shown by [130]. As the medium clutter condition differs from the low and high clutter conditions, further research will be needed to determine the cause. Possible reasons could be lack of sample size and power, or that the interaction effect is stronger for low or high clutter conditions.

For the interaction between the variables of "AR UI Clutter Level" and "Target Type", projected objects were easier to find in both the low and high clutter conditions but not the medium clutter condition. The high clutter condition shows a slightly larger difference in mean visual search time $(\mu_{AR} - \mu_{Projected} = .11s)$ between target type than the low clutter condition $(\mu_{AR} - \mu_{Projected} = .06s)$. This could imply a synergistic effect of clutter and context switching on visual search time.

In the significant interaction between "AR Object Percentage" and "Target Type", the largest difference occurs when searching for an AR object when the "AR Object Percentage" is at 50% as seen in Fig. 8. This could be because AR objects may suffer from being deprioritized in perception when users have to context switch between AR and projected objects at a high rate during a search. It could also imply that AR objects are less distinct than their projected counterparts and may all "blend together" in a search task involving a high rate of context switching. Design implications being that as the amount of AR clutter and projected clutter become more equal, it could be more difficult to find AR objects.

Mean Visual Search Time vs. Target Type and AR %

Real Target

AR Target

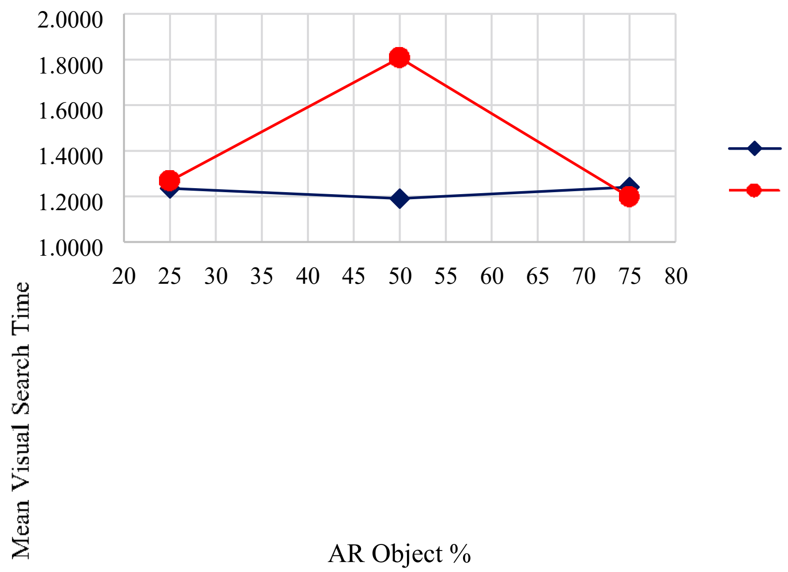


Fig. 8. Visual Search Time vs AR Object % and Target Type

The three-way interaction between “AR UI Clutter Level”, “AR Object Percentage”, and “Target Type” shows that all variables remain significant considering each other. The interaction effect is most pronounced under the combination of high “AR UI Clutter Level”, AR “Target Type”, and 50% “AR Object Percentage”. These results could have design implications as it represents an AR UI condition to avoid if possible as there is a discernable negative effect on visual search time.

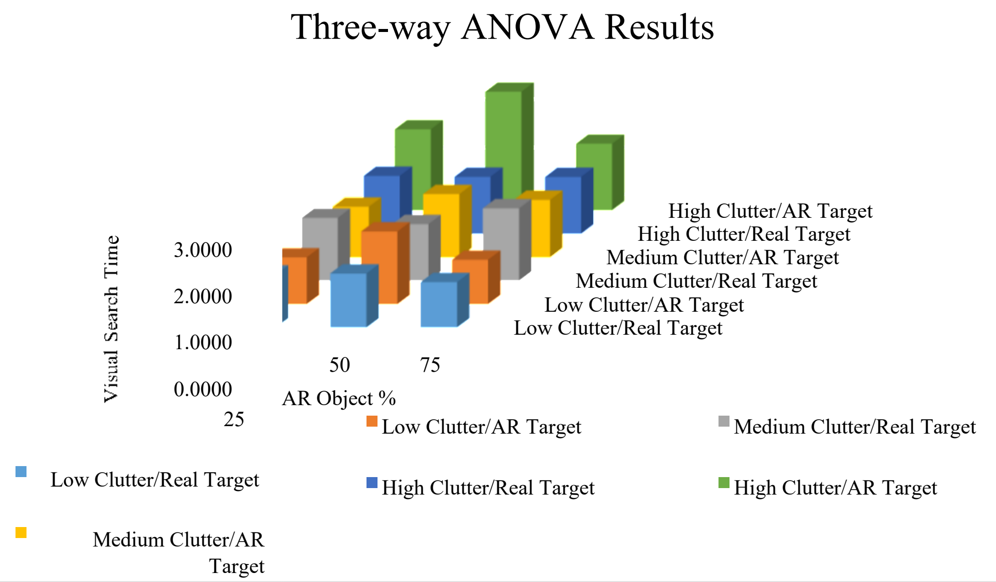


Fig. 9. Three-way ANOVA results

4.6.2 Pearson Correlation

All image analysis measures (edge density, feature congestion, and sub band entropy) of combined AR UI (projected and AR) clutter correlated with visual search time. This result agrees with previous research into image analysis measures for non-AR UIs and performance of [52], [69], [99]. Each image analysis measure showed a similar degree of positive correlation to visual search time (Edge Density: r(88)=.25, p=.017, Feature Congestion: r(88)=.27,p=.012, Sub-band Entropy: r(88)=.28, p=.008). The different measures of clutter (feature congestion, sub-band entropy, and edge density) correlate equally well in this study. This could imply that image analysis measures may be redundant to each other, so not all may be needed depending on the application. Interestingly, it is only the measures for the combined projected and AR arrays that correlates to visual search time, and not the measures for the constituent parts of the AR UI; the projected array by itself, or the AR array by itself. This implies that visual search time is dependent on overall clutter, and that in terms of a search task, clutter should be considered evenly whether it is projected or AR. This is important since it suggests that AR and projected objects add equal amounts of clutter to a UI, there is no “extra penalty” for using AR. Furthermore, we can extrapolate this to say that 2D image processing measures are viable candidates for characterizing clutter in AR UI contexts.

4.7 Post-Hoc Analysis and Discussion

4.7.1 Target Clutter and Target Eccentricity

AR UIs have many variables which need to be accounted for, and to better direct future studies, a post-hoc analysis using a two-tailed Pearson correlation test between the mean of visual search time for each trial and both target eccentricity, and target clutter level. A post-hoc power analysis was carried out using G*Power V3.1.9.7 [127] to test correlation using a two-tailed test an alpha of .05, the sample size of 90, and the calculated effect size. Results are shown in the table below.

Table 10. Pearson Correlation

Variable	**r(df) between variable and visual search time**	***p***	**Power**
Target ED	r(88)=.19	***p*=.037**	.39
Target FC	r(88)=.25	***p*=.006**	.77
Target SE	r(88)=.23	***p*=.010**	.68
Target Eccentricity	r(88)=.20	***p*=.030**	.47

Visual search time was positively correlated to all image analysis measures of clutter for the target objects, showing that it was more difficult to find a more cluttered target. This result held for both projected and AR targets, indicating that the image analysis measures of clutter match up with cognitive processing times for objects. The more complex an object is rated, the longer it takes a user to process that they have seen that object. Target eccentricity also had a positive correlation to visual search time implying that targets further from center took longer to find, which agrees with previous results analyzing traditional displays [109]–[114]. As this result comes from a posthoc test of low power, it will need to be further examined in future studies.

4.7.2 Discussion Summary

This study examined the viability of extant image analysis measures of visual clutter in the AR UI space as well as analyzing other factors that may affect visual search time such as target type and percentage of AR objects. Results indicate that extant image analysis measures of clutter (edge density, feature congestion, and sub-band entropy) are viable measures of clutter's effect on visual search time in the AR space. It is effective when applied to overall AR UI clutter, and post-hoc analysis shows that image analysis measures may also be viable predictors of visual search time when applied to target clutter. Other factors that were shown to correlate with visual search time were the "Target Type" and "AR Object Percentage". A post-hoc analysis of target eccentricity also showed that it may be correlated with visual search time. When image analysis measures were taken for only the projected object arrays or only the AR object arrays, they did not show correlation with visual search time. Overall, this study showed that clutter can be measured in AR UIs using extant techniques, and that visual search time in AR UIs is not just a function of clutter but is a multifaceted problem with several factors.

4.8 Conclusions

This work characterizes the relationship between visual search time in AR UIs and image analysis measures of clutter, as well as “AR Object Percentage” and “Target Type”. The results indicate that image analysis measures of clutter are viable for use in the AR UI space. Due to the complex nature of AR UIs, there are also several other variables such as AR object percentage and target type that affect visual search time outside of clutter. Other variables based on a post-hoc analysis of the data could be target clutter and target eccentricity.

4.9 Future Work and Limitations

This work is the first step towards creating an AR UI Visual Clutter Score algorithm that can predict visual search time by analyzing a given AR UI. The algorithm will be comprised of (n_x) factors that affect visual search time in AR UIs, and output performance as measured through visual search time. This can then be used to compare different AR UI configurations to each other.

Future studies will expand this algorithm through examining additional variables such as AR UIs with an UI of differing apparent depths, The use of three-dimensional AR objects, and a further examination of target clutter, target eccentricity and target apparent depth on visual search time. This will build a more fully featured model capable of predicting visual search time for a wider variety of applications and AR UI systems.

General Limitations of this study are detailed in Section 3.4.

A limitation of this study is that the projected objects were 2D representations of real objects displayed via a projector instead of being physical objects. Projected objects possess luminance similar to holographic objects which is different than real-world objects. Using real world objects mixed with AR objects would increase the dissimilarities of the two objects sets which could possibly lead to increased effects of the “Target Type” on visual search time. Furthermore, the differences may cause new effects, with AR objects possibly being easier to identify in a visual search task as the AR objects would possess luminance which the real-world objects lack.

While the results of this research may not yet be able to accurately predict search time based on an AR UI configuration, the results can still compare two different AR UIs and establish which one will result in better visual search time.

5 Effects of Clutter and Multiple UI Planes in Augmented Reality on Visual Search Time

Abstract - In optical see-through (OST) head mounted (HMD) augmented reality (AR) displays, information may be presented at several different apparent distances from the user. This study explores how the visual clutter of an AR UI, the AR UI Configuration (number of AR UI apparent planes and the apparent distances of the constituent AR UI planes), and the target object apparent distance affect visual search time in a semistructured search task in an AR UI. Post hoc analysis also investigates the number of AR UI planes and the effect of target clutter and location on participant visual search time. The goal of this research is to develop an algorithm capable of predicting user performance through the metric of visual search time for a given AR UI relative to another AR UI. Visual clutter is measured using image analysis measures (edge density, feature congestion, and sub-band entropy) which were specifically chosen as they can be applied to complex and naturalistic scenes as is common to experience while using an AR UI. In this study, twelve participants performed a visual search task of locating a target object in an array of objects. Participants completed this task under two different clutter levels (low, high), against twelve different AR UI configurations (AR UI plane arrays of 2m, 4m, 6m, 2m4m, 2m6m, 4m6m, 2m4m6m with targets found in each available plane of a given AR UI plane array). Task performance was measured through visual search time. Main results show significant differences in visual search time between differing AR UI configurations, and AR UI clutter levels. Image analysis measures (edge density, feature congestion, and subband entropy) of clutter for the AR UI had Pearson Correlation coefficients of r(118)=.29, r(118)=.28, and r(118)=.27 respectively with visual search time. Post-hoc testing showed that image analysis measures for the target as well as target eccentricity r(118)=.25 and the number of apparent planes r(118)=.36 also correlated to visual search time.

5.1 Objective

This study focuses on understanding and quantifying the effects of clutter in multi-plane Optical See-Through Augmented Reality User Interfaces (AR UIs). The study evaluates if image analysis measures of visual clutter can be expanded from single-plane AR UIs to multi-plane AR UIs, as well as examining the effects that multiple AR UI planes, overall AR UI clutter, and target inherent clutter have on visual search time. Image analysis measures of clutter were specifically chosen as they can be applied to complex and naturalistic images that may be found in future AR UI applications. This study also acts as an exploratory study into the effects of; the number of AR UI planes, target eccentricity, target apparent depth, and target total distance on participant visual search time in AR UIs.

5.2 Method

5.2.1 Experimental Design

The study was designed as a multiple-factor, within-subjects experimental design. It was fully crossed on the independent variables of "AR UI Clutter Level" (low and high) and randomized on "AR UI Configuration" (AR UI apparent plane arrays of: 2m, 4m, 6m, 2m4m, 2m6m, 4m6m, 2m4m6m, and target apparent distances of; 2m, 4m, 6m). This resulting "AR UI Configuration" variable has 12 levels since the values for the variable of target plane can only exist for available planes (i.e. if the AR UI apparent plane array is 2m4m, then target apparent distances can only take on values of 2m or 4m, but not 6m. The dependent variable was visual search time. An image summary of "AR UI Configuration" can be found in Fig. 10.

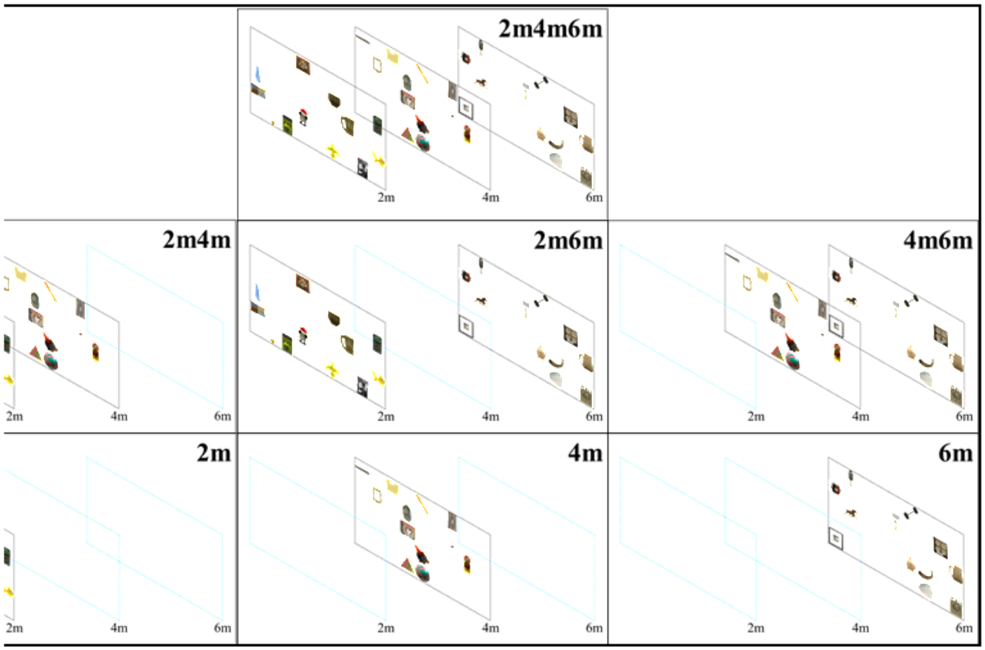


Fig. 10. AR UI configurations showing the locations of objects

The study was counterbalanced on the variable of "AR UI Clutter Level" and the presentation of "AR UI Configuration" was randomized. The dependent variable was visual search time. A guide to each condition is provided in the following table.

Table 11. Experiment Design condition Reference Guide

Condition	AR UI Clutter Level	Target Apparent Distance	AR UI Apparent Plane Array	Number of Plane(s)
1	Low	2m	2m	1
2	High	2m	2m	1
3	Low	4m	4m	1
4	High	4m	4m	1
5	Low	6m	6m	1
6	High	6m	6m	1
7	Low	2m	2m4m	2
8	High	2m	2m4m	2
9	Low	4m	2m4m	2
10	High	4m	2m4m	2
11	Low	2m	2m6m	2

12	High	2m	2m6m	2
13	Low	6m	2m6m	2
14	High	6m	2m6m	2
15	Low	4m	4m6m	2
16	High	4m	4m6m	2
17	Low	6m	4m6m	2
18	High	6m	4m6m	2
19	Low	2m	2m4m6m	3
20	High	2m	2m4m6m	3
21	Low	4m	2m4m6m	3
22	High	4m	2m4m6m	3
23	Low	6m	2m4m6m	3
24	High	6m	2m4m6m	3

There were five trials at each condition, for a total of 120 trials per participant.

5.2.2 Participants and Demographics

Institutional Review Board (IRB) approval was obtained, and twelve participants completed the study. The participants ranged in age from 23-65 years old with normal (20/20) or corrected to normal with contacts or glasses vision. There were 8 male and 4 female participants (men: mean age = 28.6; women: mean age = 38,).

5.2.3 Equipment

Equipment used in this study is detailed in Section 3.1.

5.2.4 Clutter Levels and AR UI Generation

5.2.4.1 Image analysis settings

Settings for the extant image analysis measures of clutter are detailed in Section 3.2.1.

5.2.4.2 Objects

Object selection and processing is detailed in Section 3.2.2.

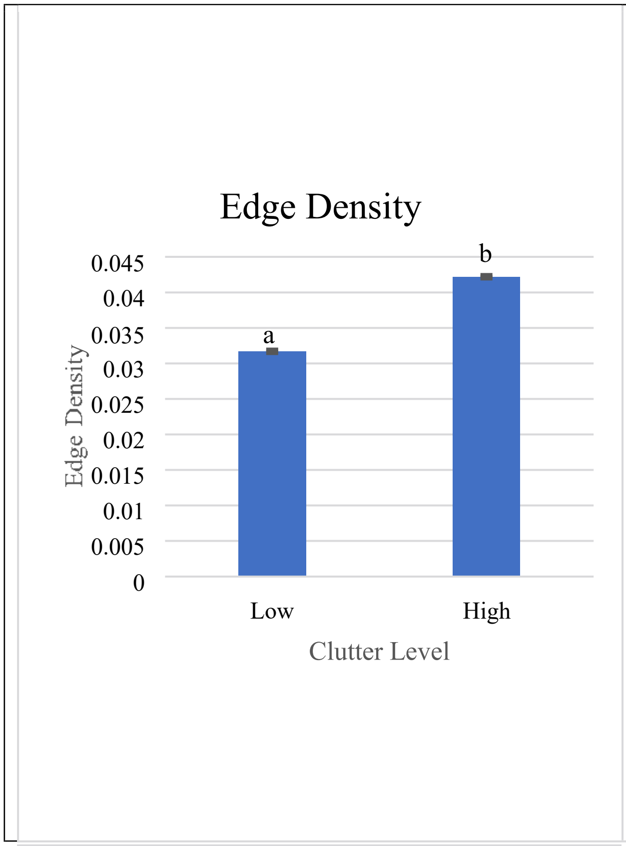
5.2.4.3 Creating AR UIs

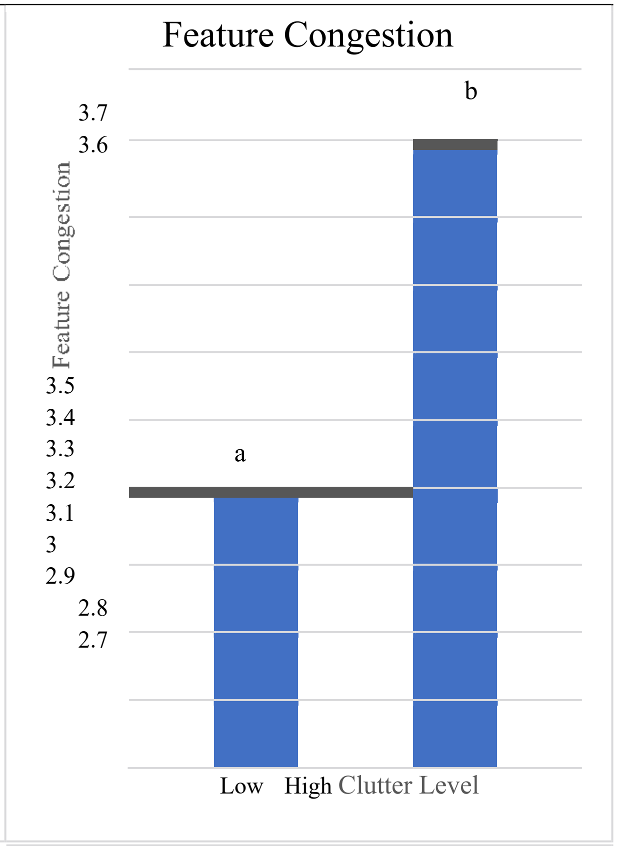
AR UI creation is detailed in Section 3.2.3.

The AR UIs were analyzed to check for within clutter level consistency, i.e., all low clutter AR UIs should have similar image analysis results. The results of this analysis are shown in the following table and figure.

Table 12. AR UI Clutter Summary (N=120)

Clutter Level	**Edge Density**		**Feature Congestion**		**Sub-band Entropy**	
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**
Low	0.0317	0.0003	3.0560	0.0164	2.8876	0.0183
High	0.0422	0.0003	3.6006	0.0171	3.1166	0.0300





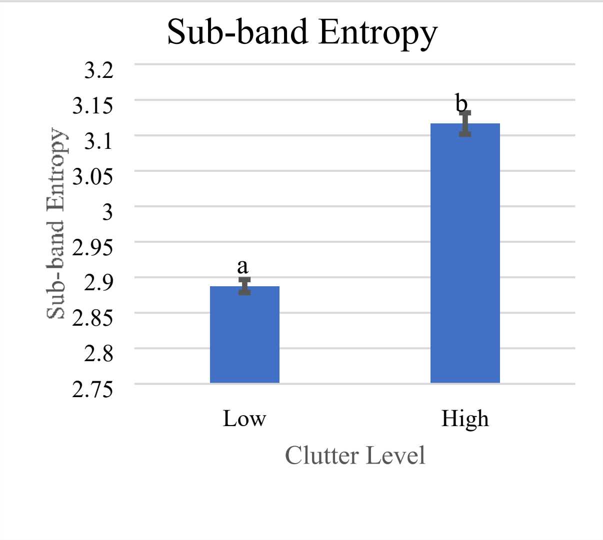


Fig. 11. Summary of different clutter metrics for low and high clutter levels, clutter levels were statistically significantly different from each other across all metrics.

5.2.5 Visual Search Task and Procedure

Participants completed a series of visual search tasks by identifying a target object within an AR UI comprised of 2D objects randomized from a collection of household objects. AR UIs were presented to participants using the HoloLens1 to appear as though they were at all combinations of two, four, and six meters from the participant. Due to the set focal plane of the HoloLens1 at approximately 2m, objects at 2m have an accommodative demand of 2m while objects at distances greater than 2m have an apparent distance that is unmatched to the HoloLens1's fixed accommodative demand of 2m. [123] demonstrated that individuals can estimate distances in the HoloLens1 of holograms, but that they may overestimate these distances for objects not on the ground.

Participants were seated in a room with ambient light levels of 20 lux. They were given a Bluetooth keyboard, seated facing a neutral wall of off-white. They were then given the HoloLens1 to put on and instructed how to adjust the device so that it fit comfortably. To complete the task, participants were shown the object they had to find in the HoloLens, then, when ready to search for this object in the AR UI, participant pressed the spacebar on a Bluetooth keyboard and were shown an AR UI comprised of objects which contained the target object (Fig. 12). Participants indicated that the target object was found by entering "f" or "j" (so that participants could use whichever hand they preferred) key on a Bluetooth keyboard (binary self-report). When the "f" or "j" key had been pressed, the program recorded the time between the AR UI being shown, and the target being indicated as being located. The participant was seated at a desk and instructed to stay as still as possible, but not precluded from moving. This approach was done to put the participants view in line with the image analysis measures of the AR UI. Despite the instructions, slight movements of the participants could reveal different views of the objects as well as indications of object depth due to shading differences or parallax. This approach results in the user experiencing sets of objects at different distances as shown in Fig. 13.

Fig. 12. Example of object AR UI, straight on view

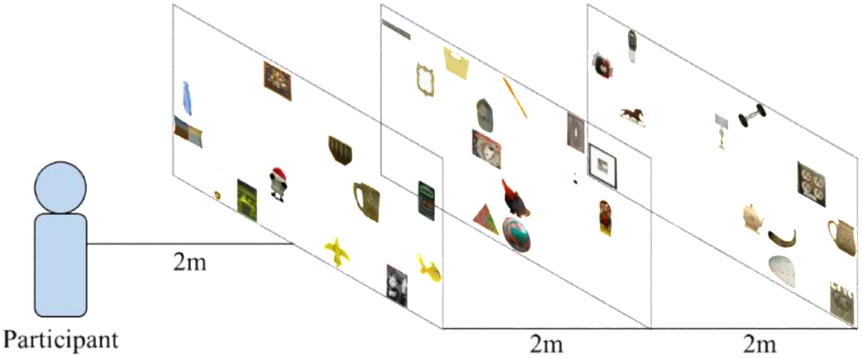


Fig. 13. Example of object AR UI, isometric view

The participant was then given instructions on the task and completed 3-5 test trial searches. During these searches, the experimenter also checked to make sure that the participant was seeing all objects correctly, i.e., objects along the edge were visible. Each participant experienced all combinations of two different "AR UI Clutter Level" (low and high) and twelve different "AR UI Configuration" (seven AR UI apparent plane arrays; 2m, 4m, 6m, 2m4m, 2m6m, 4m6m, 2m4m6m where the target was found in every available apparent plane). Each combination of "AR UI Clutter Level", and "AR UI Configuration" was known as a condition, and there were 5 trials per condition for 120 total trials. Participants verbally indicated when they were ready for each new trial and took a short rest after the 40th and 80th trials.

5.2.6 Measures

Participant performance was measured using visual search time. A detailed explanation of the collection of visual search time is found in Section 3.3.

5.3 Data Processing

Twelve participants each completed 5 trials of 24 conditions resulting in 1440 measurements taken. A detailed breakdown of the replications and conditions can be seen in the following table.

Table 13. Detailed Visual Search Task Conditions

Clutter Level	**AR UI configuration**	**Target Apparent Distance**	**Replications (5)**				
Low	2m	2m	1	2	3	4	5
	4m	4m	1	2	3	4	5
	6m	6m	1	2	3	4	5
	2m4m	2m	1	2	3	4	5
		4m	1	2	3	4	5
	2m6m	2m	1	2	3	4	5
		6m	1	2	3	4	5
	4m6m	4m	1	2	3	4	5
		6m	1	2	3	4	5
	2m4m6m	2m	1	2	3	4	5
		4m	1	2	3	4	5
		6m	1	2	3	4	5
High	2m	2m	1	2	3	4	5
	4m	4m	1	2	3	4	5
	6m	6m	1	2	3	4	5
	2m4m	2m	1	2	3	4	5
		4m	1	2	3	4	5
	2m6m	2m	1	2	3	4	5
		6m	1	2	3	4	5
	4m6m	4m	1	2	3	4	5

		6m	1	2	3	4	5
	2m4m6m	2m	1	2	3	4	5
		4m	1	2	3	4	5
		6m	1	2	3	4	5

During the experiment, some participants would self-identify errors of either forgetting the target or indicating that they had found a target before they actually had, in both of these cases the data point of search time was excluded from further analysis (23 trials lost).

Each condition (a combination of “AR UI Clutter Level” and “AR UI Configuration”) was then analyzed for outliers using the interquartile method. The interquartile range (IQR) for the data was determined then the IQR was multiplied by 1.5 (a constant used to discern outliers) and added to the third quartile, any number greater than this is a suspected outlier. This resulted in 48 outliers being identified out of 1440 measurements. After lost trials and outliers there were 1369 remaining measurements. Participant visual search times over the five trials per condition were converted to a mean visual search time per condition (24 data points/participant). For the Pearson correlation, the average visual search time across all participants was taken for each trial of each condition (120 data points).

Table 14. Summary of data points removed for each condition

Condition	**Data Points Removed**
1-Low Clutter	3
1-High Clutter	2
2-Low Clutter	3
2-High Clutter	1
3-Low Clutter	4
3-High Clutter	3
4-Low Clutter	5
4-High Clutter	4
5-Low Clutter	5
5-High Clutter	2
6-Low Clutter	1

6-High Clutter	2
7-Low Clutter	3
7-High Clutter	3
8-Low Clutter	4
8-High Clutter	4
9-Low Clutter	2
9-High Clutter	2
10-Low Clutter	2
10-High Clutter	3
11-Low Clutter	6
11-High Clutter	1
12-Low Clutter	4
12-High Clutter	2
Total	71
% of Total Observations	4.93%
Minus Self-Reported	48

5.4 Analysis

Prior to analysis all conditions were checked for normality using the Shapiro-Wilks Normality test and an inspection of the Normal QQ Plot. All conditions were found to be normal except for condition 24 (high clutter, 2m4m6m plane array, and the target located at an apparent distance of 6m from the participant). A repeated measure ANOVA is robust to some deviations of normality though. A summary of the tests and plots can be seen in Appendix 9.2. All statistics were conducted using *IBM SPSS 26* and $\alpha=0.05$.

Two statistical modeling approaches were taken to analyze the model. First was a two-way repeated measures ANOVA of the independent variables of “AR UI Clutter Level” and “AR UI Configuration” on the dependent variable visual search time. The second was using a Pearson correlation test to determine if continuous independent variables (clutter measures) correlated with the dependent variable of mean visual search time. Post hoc analysis was done on the independent variables of “Target Clutter Level”, “Target Apparent Distance”, “Number of Apparent Planes”, and aspects of target position.

5.5 Results

5.5.1 Main Results

5.5.1.1 Two-way repeated measures ANOVA

A two-way repeated measurement ANOVA was carried out between “AR UI Clutter Level” and “AR UI Configuration”

Table 15. Tests of Sphericity

Within Subjects Effect					**Epsilon**		
Variable	**Mauchly's W**	**Chi-Square**	**df**	***p***	**Greenhouse-Geisser**	**Huynh-Feldt**	**Lower-bound**
AR UI Clutter Level	1.00	0.00	0	-	1.00	1.00	1.00
AR UI Configuration	0.00	148.56	65	*p*<.001	0.24	0.32	0.09
AR UI Clutter Level * AR UI Configuration	0.00	119.02	65	*p*<.001	0.34	0.53	0.09

Table 16. Summary of main and interaction effects

Variable		**Sum of Squares**	**F**	***p***	***η*2**
AR UI Clutter Level	Sphericity Assumed	1.89	F(1,11)=5.74	***p*=.035**	.34
	Greenhouse-Geisser	1.89	F(1,11)=5.74	***p*=.035**	.34
	Huynh-Feldt	1.89	F(1,11)=5.74	***p*=.035**	.34
	Lower-bound	1.89	F(1,11)=5.74	***p*=.035**	.34
AR UI Configuration	Sphericity Assumed	12.99	F(11,11)=7.57	***p*<.001**	.41
	Greenhouse-Geisser	12.99	F(2.65,11)=7.57	***p*<.001**	.41
	Huynh-Feldt	12.99	F(3.56,11)=7.57	***p*<.001**	.41
	Lower-bound	12.99	F(1,11)=7.57	***p*=.019**	.41
AR UI Clutter Level * AR UI Configuration	Sphericity Assumed	12.65	F(11,11)=10.38	***p*<.001**	.49
	Greenhouse-Geisser	12.65	F(3.7,11)=10.38	***p*<.001**	.49
	Huynh-Feldt	12.65	F(5.82,11)=10.38	***p*<.001**	.49
	Lower-bound	12.65	F(1,11)=10.38	***p*=.008**	.49

5.5.1.2 Pearson correlation

A two-tailed Pearson correlation test was carried out between the mean of visual search time for each trial and individual image analysis measures of clutter (edge density, feature congestion, and sub-band entropy) for AR UIs. A post-hoc power analysis was carried out using G*Power V3.1.9.7 [127] using the "Exact Test Family" and the "Correlation: Bivariate normal model" to test correlation using a two-tailed test an alpha of .05, the sample size of 120, and the calculated effect size. Results are summarized in the following table.

Table 17. Pearson Correlation Image Analysis Measures & Array Clutter

Variable	**r(df) between variable and search time**	***p***	**Power**
AR UI Edge Density	r(118)=.29	***p*=.002**	.90
AR UI Feature Congestion	r(118)=.28	***p*=.002**	.87
AR UI Sub-band Entropy	r(118)=.27	***p*=.003**	.84

5.6 Discussion

5.6.1 Two-way repeated measures ANOVA

5.6.1.1 Main effects

In the two-way repeated measures ANOVA a significant main effect was found for the independent variables of "AR UI Clutter Level" and "AR UI Configuration". The effect of AR UI clutter agrees with previous research in AR UIs [124], [125]. As well as pervious work regarding the use of image analysis techniques as measures of clutter [52], [69], [100]. It also agrees with other UI results of significance of clutter on visual search time [45], [52]–[55], [69]–[72].

The importance of this finding is not only that clutter affects visual search time in AR UIs, which would be expected by the literature and study one, but that image analysis measures of clutter are viable in more complex AR UIs. While study one focused on the application of image analysis measures of clutter for AR UIs comprised of objects at a single apparent distance, this study shows that the measures work equally as well when used on an AR UI comprised of UI objects at multiple apparent distances. This is important as clutter can affect search time, which is an important metric for many domains seeing an increase in AR UI usage such as driving [126], aviation [128], and even warehouse operations [8], [91]. These results support the need for designing AR UIs of low clutter.

The significant effect of “AR UI Configuration” on clutter shows that the layout and apparent depths of the objects comprising the AR UI have an effect on visual search time. This could be because of the need for participants to distance switch while searching for the target. That is, verge to different apparent distances while visually searching for the target. This is different than focal distance switching due to the fixed focal demand of the HoloLens1. The result of distance switching while searching the AR UI for the target agrees with similar results of focal distance switching having a negative effect on performance [132], [133], but contrary to results from [129] that found that focal distance switching has no significant effect on visual search time.

5.6.1.2 Interaction effects

A significant interaction effect was found between “AR UI Clutter Level” and “AR UI Configuration”. This interaction was most prominent for the “AR UI Configuration” of objects being found at apparent distances of 2m, 4m, and 6m with the target being found at 4m and 6m. This result shows that visual search time is not only influenced by visual clutter and the number of planes of differing apparent distances, but by both simultaneously.

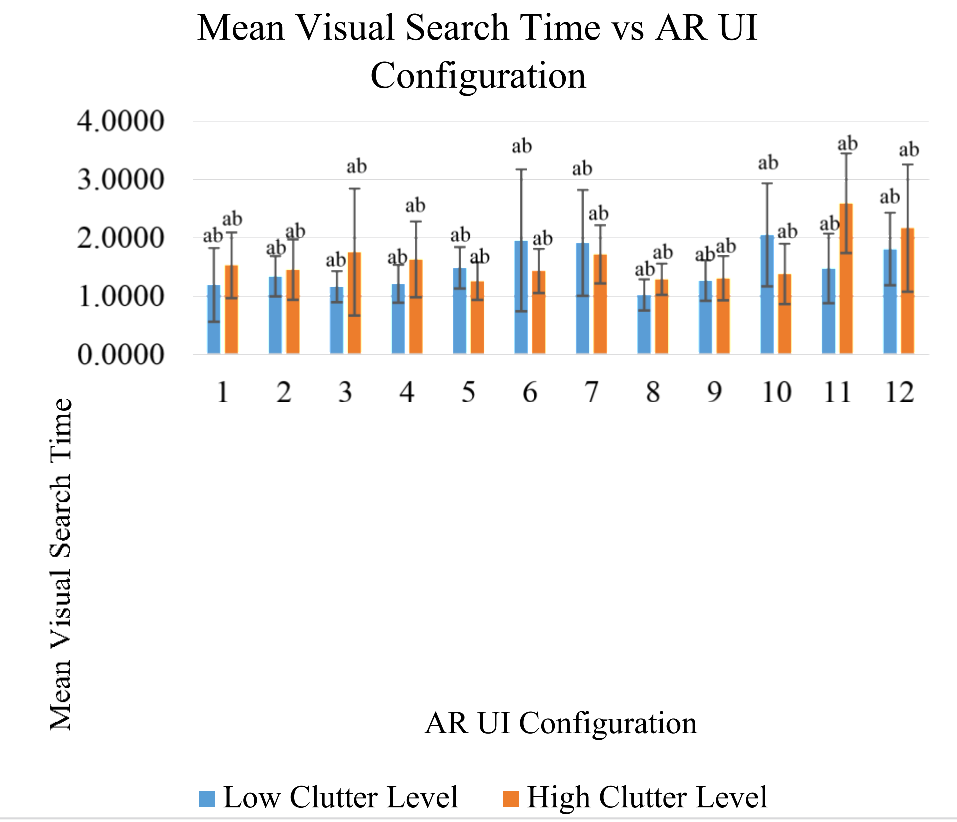


Fig. 14. Mean visual search time vs "AR UI Configuration" for each "AR UI Clutter Level". The ANOVA found a significant effect of "AR UI Configuration" on visual search time

5.6.2 Pearson Correlations

All image analysis measures (edge density, feature congestions, and sub-band entropy) of AR UI clutter correlated with visual search time. This result agrees with previous research into image analysis measures and performance of [52], [69], [99], as well as with previous research in AR UIs [125]. Each image analysis measure had a similar degree of positive correlation to visual search time (edge density: r(118)=.29, p=.002, feature congestion: r(118)=.28, p=.002, sub-band entropy: r(118)=.27, p=.003). This similarity level of correlation could imply that image analysis measures may be redundant to each other. This has implications for future applications as some measures may be easier to implement than others based on a given application, so not all may be needed to adequately account for the role of visual clutter in AR UIs on visual search time. of interest in order to identify candidates for future studies.

5.7 Post-Hoc Analysis and Results

AR UIs have many variables which need to be accounted for. To better direct future studies, the following post-hoc analysis was carried out. A two-tailed Pearson correlation test was carried out between the mean of visual search time for each trial and individual image analysis measures of clutter (edge density, feature congestion, and sub-band entropy) for targets, target position (eccentricity, apparent depth, and target total distance), and the number of planes. A post-hoc power analysis was carried out using G*Power V3.1.9.7 [127] to test correlation using a two-tailed test an alpha of .05, the sample size of 120, and the calculated effect size. Results are summarized below.

Table 18. Pearson Correlation Image Analysis Measures and Target

Variable	**r(df)**	***p***	**Power**
Target Edge Density	r(118)=.35	***p*<.001**	.98
Target Feature Congestion	r(118)=.34	***p*<.001**	.97
Target Sub-band Entropy	r(118)=.20	***p*=.032**	.46
Target X Angle	r(118)=.04	***p*=.652**	1.00
Target Y Angle	r(118)=-.01	***p*=.895**	1.00
Target Z	r(118)=.04	***p*=.681**	1.00
Target Eccentricity	r(118)=.25	***p*=.006**	.77
Target XYZ	r(118)=.14	***p*=.139**	.05
Number of Planes	r(118)=.36	***p*<.001**	.98

5.7.1 Post Hoc Discussion

Post-hoc testing showed that visual search time was positively correlated to image analysis measures of clutter measures for the target itself, which agrees with previous work [125]. Edge density; r(118)=.35, p<.001 and feature congestion; r(118)=.34, p<.001 showed slightly better results than sub-band entropy; r(118)=.20, p=.032 . This result agrees with [29], [69], [134], [135] as it takes longer to process that more complex target has been found, leading to a longer visual search time.

This result is important as it shows that not only is the overall clutter of the AR UI important, but almost as important is the clutter of the target object. Because of this, target clutter will be an important variable to analyze moving forward.

When taken by themselves the targets' horizontal angle (X), vertical angle (Y), apparent depth (Z), and total distance did not significantly correlate with visual search time. The target eccentricity however did show a positive correlation with the visual search time r(118)=.25. This result agrees with previous work [109]–[114] which compared the effects of eccentricity on visual search time. While a post-hoc test, this result shows that the location of the target within the field of view of the AR UI could be an important variable to examine moving forward. Another limitation to this finding is that the narrow field of view provided by the HoloLens1 device also limits interpretation as none of the objects would fall into what would be considered the periphery of the field of view.

The "Number of Apparent Planes" also showed a correlation (r(118)=.36, *p*<.001) to visual search time in post hoc testing. This result agrees with the results of the variable "AR UI Configuration" and visual search time, where number of planes is embedded into the "AR UI Configuration" variable. This could be due to a focal distance switching effect as seen in of [132], [133].

5.8 Conclusions

5.8.1 Contribution

The refinement of the AR UI Visual Clutter Score algorithm will be the main contribution to the literature. Other n_x factors will be added to the algorithm to account for the effects of the number of AR UI planes as well as other factors.

$$Performance = f(AR\ Clutter, Background\ Clutter, n_1, n_2, \cdots, n_n) \tag{1}$$

The shortest visual search time would be expected for a target that has low clutter in an AR UI of low overall clutter that is located in the center of the field of view when there is only one UI plane. The longest visual search time would be expected for the opposite of this; a target that has high clutter in an AR UI of high overall clutter that is located far from the center of the field of view when there are three UI planes.

This work helps to further previous research [124], [125] into developing an AR UI interface score by identifying the significant variables that affect visual search time.

$$AR\ UI\ Score = w_1(Target\ Clutter) + w_2(Overall\ Clutter) + w_3\left(\sum Planes\right) \tag{2}$$

While not all relationships are strong between the dependent variable of visual search time and the independent variables are significant at the $\alpha = 0.05$ level, they have significance at the $\alpha = 0.1$ or $\alpha = 0.2$ level. This matters in the context of the overall goal of this research, which is to establish a tool for comparing different AR UIs to each other. While the results of this research may not yet be able to accurately predict visual search time (in seconds) for a specific UI configuration, the results can still compare two different AR UIs and establish which one will likely result in better user visual search time.

5.9 Future Work and Limitations

This study builds on previous work in analyzing the effectiveness of extant image analysis techniques of quantifying clutter. The addition of more UI planes expands this to a more naturalistic setting. Future studies will expand on this by moving to 3D holographic objects and an increase in apparent AR UI depths.

General Limitations of this study are detailed in Section 3.4

Limitations specific to this study were a limited amount of AR UI apparent planes and setting the nearest AR UI plane distance at 2m. Using 2m as the shortest apparent plane depth and a range of 2m to 6m with only three planes limits the amount of possible verging a participant could do while searching for a target. The scope of this study necessitated limiting the amount of AR UI planes in the conditions of multiple AR UI planes as the focus was on the difference between a single plane AR UIs and a non-single plane AR UIs.

6 The Effects of User Interface Clutter in Conjunction with Target Clutter and Target Location on Visual Search Time in Optical See-Through Augmented Reality Displays

Abstract - In optical see-through (OST) head mounted (HMD) augmented reality (AR) displays, information may be presented at several different apparent distances from the user. This study explores how visual clutter of the AR user interface (UI), the clutter of a target object the user is searching for, as well as target location affect visual search time. The goal of this research is to develop an algorithm capable of predicting relative user performance (through the metric of visual search time) through analyzing the properties of a given AR UIs. Extant image analysis techniques of feature congestion, edge density, and sub-band entropy are specifically chosen to quantify clutter, as they can be applied to complex and naturalistic scenes, as is common to experience while using an AR UI. Extant image analysis measures of clutter are specifically chosen, as they can be applied to complex and naturalistic scenes, as is common to experience while using an AR UI. In this experiment, twelve participants performed a visual search task of locating a target object in an array of objects, where the array of objects represents the AR UI, and the target object would be an item of interest. Participants completed this task under two different UI clutter levels (low, high), two different target clutter levels (low, high), two different target depths (near to user, far to user), and two different target AR UI location categories (center of UI, edge of UI). ANOVA shows longer visual search times for AR UIs deemed as high clutter versus low clutter and for targets that were considered farther in apparent depth than nearer. Analysis also showed visual search time was positively correlated to measures of total AR UI clutter and to the edge density measure of target clutter as well as the target eccentricity. Visual search time showed no significant correlation to target depth or total target distance from user. Results from this work can be used to compare the predicted visual search efficacy of different AR UIs without the need for human subject testing.

6.1 Objective

Previous research has shown that image analysis measures of clutter are viable in the complex AR UI space and that clutter does have an effect on visual search time [125]. Other factors that may affect visual search time were analyzed such as the target location in AR UI, target eccentricity, target apparent depth, and target clutter level. Exploring the new independent variables of target location in the AR UI, target eccentricity, target apparent depth, and target clutter builds upon previous research to improve upon an algorithm that can analyze a given AR UI and predict visual search time without the need for human subject testing. The algorithm can also be streamlined to dynamically alter an AR UI based on user visual search time needs.

6.2 Method

6.2.1 Experimental Design

The study was designed as a multiple-factor, within-subjects experimental design. The study was fully crossed on the independent variables of: "AR UI Clutter Level" (low and high), "Target Clutter Level" (low and high), "Target AR UI Location" (center and edge), and "Target Depth Level" (near and far). This experimental design resulted in 16 conditions. The dependent variable was visual search time. The experiment used randomization instead of counterbalancing, and there were five trials at each condition, for a total of 80 trials per participant.

6.2.2 Participant Recruitment and Demographics

Institutional Review Board (IRB) approval was obtained, and twelve participants completed the series of experiments. The participants ranged in age from 23-65 years old with normal (e.g., 20/20) or corrected to normal with contacts or glasses vision. There were 8 male and 4 female participants (men: mean age = 28.6; women: mean age = 38,).

6.2.3 Equipment

Equipment used in this study is detailed in Section 3.1.

6.2.4 Clutter Levels and AR UI Generation

6.2.4.1 Image analysis settings

Settings for the extant image analysis measures of clutter are detailed in Section 3.2.1.

6.2.4.2 Objects

Object selection and processing is detailed in Section 3.2.2.

6.2.4.3 Creating AR UIs

AR UI creation is detailed in Section 3.2.3.

The AR UIs were analyzed to check for within clutter level consistency, i.e., all low clutter AR UIs should have similar image analysis results. The results of this analysis are shown in the following table and figure.

Table 19. AR UI Clutter Summary (N=80)

		Edge Density	Feature Congestion	Sub-Band Entropy
AR UI Clutter Level Low	Mean	0.0317	3.0560	2.8876
	SD	0.0003	0.0164	0.0183
AR UI Clutter Level High	Mean	0.0422	3.6006	3.1166
	SD	0.0003	0.0171	0.0300

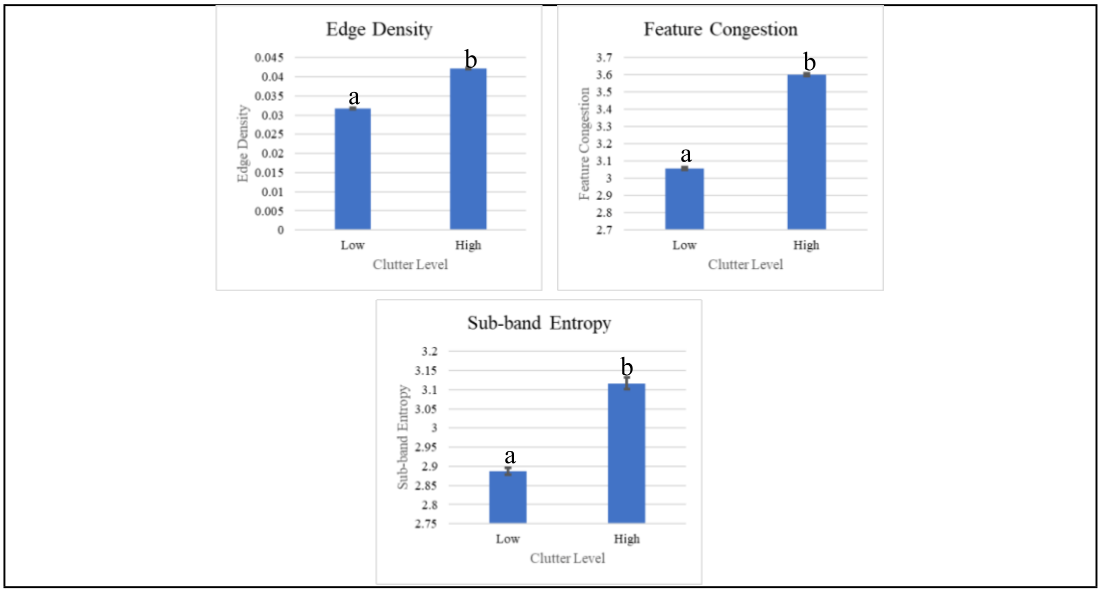


Fig. 15. Summary of different clutter metrics for low and high AR UI clutter levels. AR UI clutter levels were significantly different from each other for all image analysis measures of clutter.

6.2.5 Visual Search Task and Procedure

Participants completed a series of visual search tasks by identifying a 3D target object within an AR UI comprised of 3D objects randomized from a collection of household objects. AR UIs were presented to participants using the HoloLens1 at varying apparent distances so that objects would appear at near (2m, 2.5m, 3m, and 3.5m) or far (4.5m, 5m, 5.5m, 6m) distances The 4m distance was excluded for condition balancing purposes and so there would be a greater difference between near and far objects. The near distance of 2m was chosen to be the minimum as that is the fixed optical depth of the HoloLens1. AR UI planes were placed at apparent distance intervals of 0.5m out to 6m to simulate an AR UI of multiple apparent depths. A representation of the layout of the UI in respect to the participant can be seen in Fig. 16. Due to the set focal plane of the HoloLens1 at approximately 2m, objects at 2m have an accommodative demand of 2m while objects at distances greater than 2m have an apparent distance that is unmatched to the HoloLens1's fixed accommodative demand of 2m. [123] demonstrated that individuals can estimate distances in the HoloLens1 of holograms, but that they may overestimate these distances for objects not on the ground.

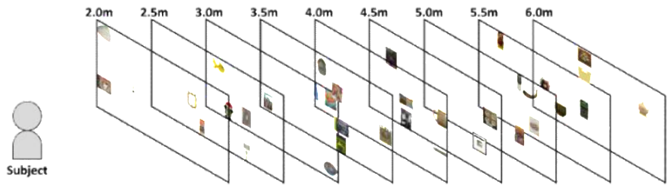


Fig. 16. Isometric view of the participant and the AR UI layout.

Participants were seated in a room with ambient light levels of 20 lux. They were given a Bluetooth keyboard, seated facing a neutral wall of off-white. They were then given the HoloLens1 to put on and instructed how to adjust the device so that it fit comfortably. To complete the task, participants were shown the object they had to find in the HoloLens, then, when ready to search for this object in the AR UI, participant hit the spacebar on a Bluetooth keyboard and were shown an AR UI comprised of objects which contained the target object (Fig. 17). Participants indicated that the target object was found by entering “f” or “j” (so that participants could use whichever hand they preferred) key on a Bluetooth keyboard (binary self-report). When the “f” or “j” key had been hit, the program recorded the time between the AR UI being shown, and the target being indicated as being located. The participant was seated at a desk and instructed to stay as still as possible, but not precluded from moving. This approach was done to put the participants view in line with the image analysis measures of the AR UI. Despite the instructions, slight movements of the participants could reveal different views of the objects as well as indications of object depth due to shading differences or parallax. This approach results in the user experiencing sets of objects at different distances as shown in Fig. 16.

Fig. 17. Participant view of AR UI.

The participant was then given instructions on the task and completed 3-5 test trial searches. During these searches, it was also checked to make sure that the participant was seeing all objects correctly, i.e., objects along the edge were visible. Each participant experienced all combinations of two different “AR UI Clutter Level” (low and high) and two different “Target Clutter Level” (low and high) two different “Target AR UI Location” (center and edge) and two different depth levels (near and far), where the target was found in every available combination of independent variables. Each combination of independent variables was known as a condition, there were 16 conditions, and 5 trials per condition for 80 trials/participant. Participants verbally indicated when they were ready for each new trial.

6.2.6 Independent Variables

The variable of “AR UI Clutter Level” was defined as a discrete variable of two levels, low and high. A detailed explanation of calculating “AR UI Clutter Level” can be found in the previous section. “Target Clutter Level” was established as follows. Since both low clutter AR UIs and high clutter AR UIs would experience both low and high clutter targets, targets had to come from the shared objects (10-36). A balance had to be struck in providing enough object variance so that a participant would not learn to search for the same one or two objects, while also providing enough separation in the target clutter levels for there to be a meaningful difference. Using the 11 most cluttered shared target objects (objects 26-36) and the 11 least cluttered shared target objects (objects 10-20) satisfied this. A summary of the results of image analysis measures for the set of high clutter target objects and low clutter target objects is found in the following table and figures.

Table 20. Target Clutter Summary

		Edge Density	Feature Congestion	Sub-Band Entropy
Target Clutter Low	Mean	0.0057	1.6199	2.5887
	SD	0.0022	0.1769	0.5149
Target Clutter High	Mean	0.0413	3.3749	3.4209
	SD	0.0278	1.2485	0.5436

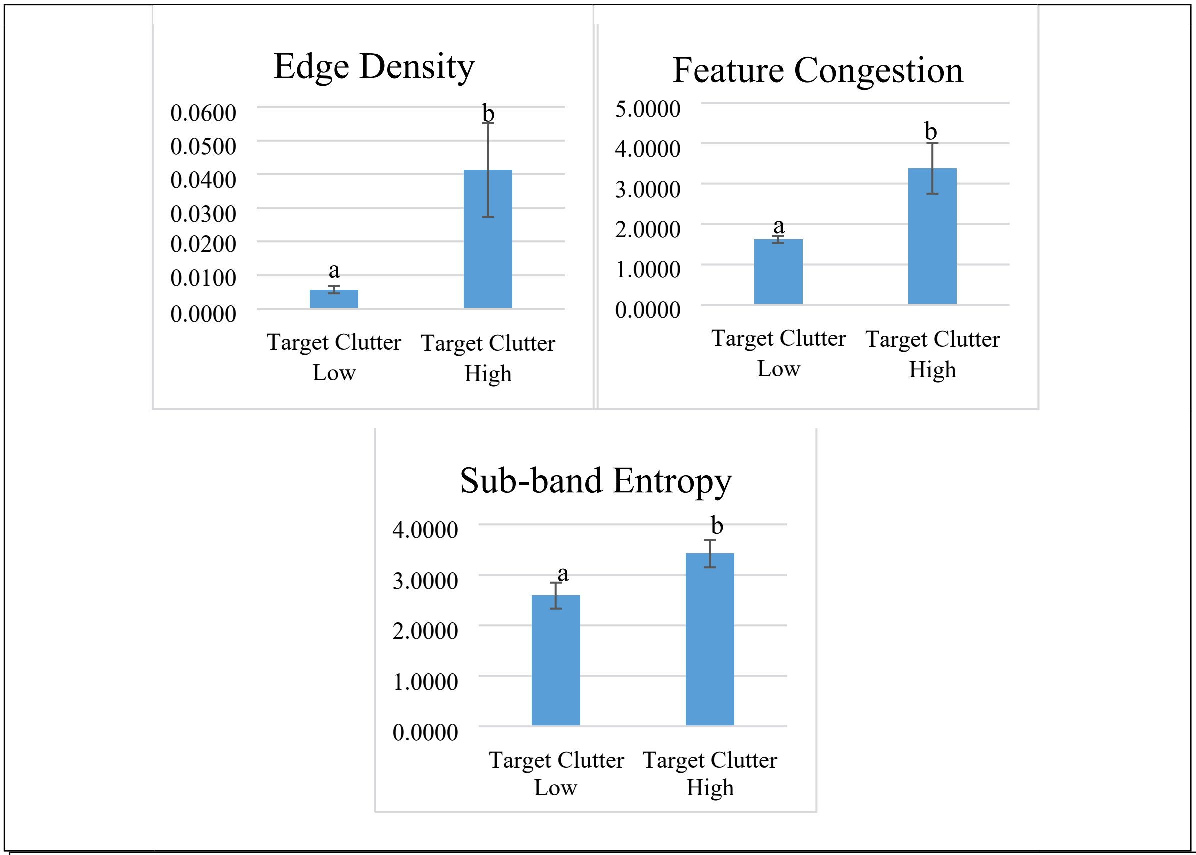


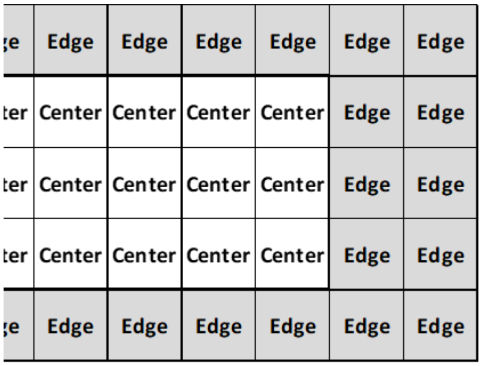
Fig. 18. Summary of different clutter measures for low and high clutter target sets. Target clutter levels were significantly different from each other across all image analysis measures of clutter.

“Target AR UI Location” was defined as a discrete variable with two levels, center and edge. Edge positions were defined as the top and bottom rows as well as the farthest two rows on the right or the left as seen in Fig 19. A related continuous variable was “Target Eccentricity” where the eccentricity was calculated as the visual angle of the target from the center of the AR UI.

The variable of target depth was defined as both a discrete and continuous independent variable. As a discrete variable it is designated “Target Depth Level” and has two levels defined as defined as: near ≤3.5m or far ≥4.5m. As a continuous variable it is designated “Target Depth” where the depth is the apparent distance of the target.

“Target Total Distance” was also defined as a continuous variable and calculated as this involved the eccentricity as well as target depth from the user or depicted mathematically in Equation (3) as:

$$Total\ Target\ Distance = \frac{Target\ Depth}{\cos(Target\ Eccentricity)} \qquad (3)$$



ge	Edge	Edge	Edge	Edge	Edge	Edge
ter	Center	Center	Center	Center	Edge	Edge
ter	Center	Center	Center	Center	Edge	Edge
ter	Center	Center	Center	Center	Edge	Edge
ge	Edge	Edge	Edge	Edge	Edge	Edge

Fig. 19. Diagram of Center vs Edge Positions

6.2.7 Measures

Participant performance was measured using visual search time. A detailed explanation of the collection of visual search time is found in Section 3.3.

6.3 Data Processing

Twelve participants each completed 5 trials of 16 conditions resulting in 960 measurements taken. Of these 960 data points, 12 were lost due to self-reported errors from the participants. Each condition (a combination of "AR UI Clutter Level", "Target Clutter Level", "Target AR UI Position", and "Target Depth Level") was then analyzed for outliers using the interquartile method. The interquartile range (IQR) for the data was determined then the IQR was multiplied by 1.5 (a constant used to discern outliers) and added to the third quartile, any number greater than this is a suspected outlier. This resulted in 40 outliers being identified out of 960 measurements. After lost trials and outliers, there were 908 remaining measurements. For the ANOVA, participant visual search times over the five trials per condition were averaged for the mean visual search time per condition per participant (16 data points/participant and 192 data points total). For the Pearson correlation, the average visual search time across all participants was taken for each trial of each condition (80 data points).

6.4 Analysis

Prior to analysis all conditions were checked for normality using the Shapiro-Wilks Normality test and an inspection of the Normal QQ Plot. Visual search time was tested for normality using the Shapiro-Wilks Normality test and an inspection of the Normal QQ Plot. The test did not show evidence of non-normality (W=.88, p<.001). Since each variable only has two levels, sphericity is met. All statistics were conducted using IBM SPSS 26 and α=0.05.

Two statistical modelling approaches were taken to analyze the model. First was a four-way repeated measures ANOVA of the independent variables of; "AR UI Clutter Level", "Target Clutter Level", "Target AR UI Position", and "Target Depth Level" on the dependent variable of visual search time. The second was using a Pearson correlation test to determine if continuous independent variables (AR UI clutter measures, target clutter measures, and target eccentricity) correlated with the dependent variable of visual search time. Post hoc analysis was done on the independent variable of target total distance.

6.5 Results

6.5.1 Four-way repeated measures ANOVA

A four-way repeated measurement ANOVA was carried out between the independent variables of "AR UI Clutter Level", "Target Clutter Level", "Target Eccentricity Level", and "Target Depth Level" on the dependent variable of visual search time. Because all variables only had two levels, assumptions of sphericity were not violated.

Table 21. Summary of main and interaction effects.

Variable	Sum of Squares	df	F	p	η_2
ARUIClutterLevel	7.75	1.00	39.74	***p*<0.001**	0.82
TargetClutterLevel	0.32	1.00	2.53	*p*=.15	0.22
TargetARUIPosition	0.05	1.00	0.24	*p*=.64	0.03

TargetZ	1.33	1.00	5.70	**_p_=.04**	0.39
ARUIClutterLevel * TargetClutterLevel	1.67	1.00	17.07	**_p_<0.001**	0.65
ARUIClutterLevel * TargetARUIPosition	0.06	1.00	0.68	_p_=.43	0.07
ARUIClutterLevel * TargetZ	1.44	1.00	6.72	**_p_=.03**	0.43
TargetClutterLevel * TargetARUIPosition	0.03	1.00	0.24	_p_=.64	0.03
TargetClutterLevel * TargetZ	0.22	1.00	2.65	_p_=.14	0.23
TargetARUIPosition * TargetZ	0.20	1.00	0.75	_p_=.41	0.08
ARUIClutterLevel * TargetClutterLevel * TargetARUIPosition	0.82	1.00	5.79	**_p_=.04**	0.39
ARUIClutterLevel * TargetClutterLevel * TargetZ	0.07	1.00	0.50	_p_=.50	0.05
ARUIClutterLevel * TargetARUIPosition * TargetZ	0.00	1.00	0.00	_p_=.96	0.00
TargetClutterLevel * TargetARUIPosition * TargetZ	0.20	1.00	4.22	_p_=.07	0.32
ARUIClutterLevel * TargetClutterLevel * TargetARUIPosition * TargetZ	0.79	1.00	6.82	**_p_=.03**	0.43

6.5.2 Pearson Correlation

A two-tailed Pearson correlation test was carried out between the mean of visual search time for each trial and individual image analysis measures of clutter (edge density, feature congestion, and sub-band entropy) for AR UIs and targets. A post-hoc power analysis was carried out using G*Power V3.1.9.7 [127] to test correlation using a two-tailed test an alpha of .05, the sample size of 80, and the calculated effect size. Results are summarized below.

Table 22. Pearson Correlation Summary

Variable	**r(df) between variable and search time**	**p**	**Power**
AR UI ED (n=80)	r(78)=.54	**_p_<.001**	1.00
AR UI FC (n=80)	r(78)=.54	**_p_<.001**	1.00
AR UI SE (n=80)	r(78)=.53	**_p_<.001**	1.00
Target ED (n=80)	r(78)=.13	_p_=.238	.22
Target FC (n=80)	r(78)=.07	_p_=.567	.09
Target SE (n=80)	r(78)=-.06	_p_=.596	.08

Target Z (n=80)	r(78)=-.19	*p*=.086	.41
TargetEccentricity (n=80)	r(78)=.29	***p*=.010**	.74
Target XYZ (n=80)	r(78)=-.19	*p*=.088	.40

6.6 Discussion

6.6.1 Four-way repeated measures ANOVA

6.6.1.1 Main effects

In the four-way repeated measures ANOVA a significant effect was found for the independent variables of “AR UI Clutter Level” and “Target Depth Level”. The effect of AR UI clutter agrees with previous research in single plane AR UIs [124], [125]. As well as pervious work regarding the use of image analysis techniques as measures of clutter [52], [69], [100]. It also agrees with other UI results of significance of clutter on visual search time [45], [52]–[55], [69]–[72].

The importance of this finding is not that clutter affects visual search time in AR UIs, which would be expected by the literature, but that the image analysis measures of clutter are viable in a complex AR UI space and that AR UI clutter as a significant effect on visual search times. The effect of clutter level on visual search time is important since many domains which see uses of AR have visual search time as an important metric, such as driving [126], aviation [128], and even warehouse operations [8], [91]. These results support the need for designing AR UIs of low clutter.

The significant effect of the variable of “Target Depth Level” where far targets have a longer visual search time than near targets is likely due to the need of participants to distance switch while searching for the target. That is, verge to different apparent distances while visually searching for the target. This is different than focal distance switching due to the fixed focal demand of the HoloLens1. The result of distance switching while searching the AR UI for the target agrees with similar results of focal distance switching having a negative effect on performance [132], [133], but contrary to results from [129] that found that focal distance switching has no significant effect on visual search time.

The independent variables of “Target Clutter Level” and “Target AR UI Position” did not have a significant effect on visual search time when viewed as discrete variables for the four-way repeated measures ANOVA. The “Target AR UI Position” variable not having a significant effect may be explained by the limited field of view of the HoloLens. The average field of view of an individual is 200°H by 135°V [136] where the HoloLens is only 30°H and 17.5°V. This limited field of view means that objects that were located on the edge of the display still fell in the center of the field of view and not the periphery.

The variable of “Target Clutter Level” not having an effect is also of interest as it would be assume that a longer processing time is needed to recognize the target object [29], [69] and that should lead to longer visual search times of finding the target object. This finding disagrees with the research that the more complex a target is, the longer it takes to identify that target [134], [135]. The implications of this are that it is the overall clutter of a complex AR UI that matters much more than the clutter of any given object that comprises the AR UI.

6.6.1.2 Interaction effects

A significant interaction effect was found between; (AR UI Clutter Level)*(Target Clutter Level), (AR UI Clutter Level)*(Target Depth), (AR UI Clutter Level)*(Target Clutter Level)*(Target AR UI Position), and (AR UI Clutter Level)*(Target Clutter Level) *(Target AR UI Position)*(Target Depth Level).

For the significant interaction of (AR UI Clutter Level)*(Target Clutter Level) it is seen that for a low “AR UI Clutter Level” condition, the visual search time improves for the high “Target Clutter Level” condition, while for the high “AR UI Clutter Level” condition, the visual search time slightly increased when moving from the low “Target Clutter Level” condition to the high “Target Clutter Level” condition as shown in Fig. 20. A reason for this could be that in a situation where the AR UI has low clutter, a high clutter target stands out more and is quicker to find, the target could be thought of as being more visual interesting than its surroundings. Whereas in an AR UI with high clutter, the clutter level of the target does not set it apart from its surroundings.

Fig. 20. AR UI clutter vs target clutter interaction, target clutter value of 1 corresponds to a low clutter and 2 corresponds to a high clutter

For the significant interaction of (AR UI Clutter Level)*(Target Depth Level) is interesting as there is a significant effect of "Target Depth Level" on visual search time, and a Pearson Correlation shows there to be no significant correlation between "Target Depth" and visual search time. This could mean that there is a synergistic effect of "AR UI Clutter Level" and "Target Depth Level", or that "AR UI Clutter Level" overwhelms the factor of "Target Depth Level" when viewed simultaneously.

The three-way interaction between (AR UI Clutter Level)*(Target Clutter Level)*(Target AR UI Position) implies that the "Target AR UI Position" variable is only significant, when both "AR UI Clutter Level" and "Target Clutter Level" variables are taken into account. The interaction effect seems most pronounced under the combination of high "AR UI Clutter Level" condition and the high "Target Clutter Level" condition as seen in Fig. 21. It is possible that there could be a hierarchy in design where the location of target object in an AR UI only affects visual search time if both the AR UI are highly cluttered and the target is highly cluttered. This would need further research though.

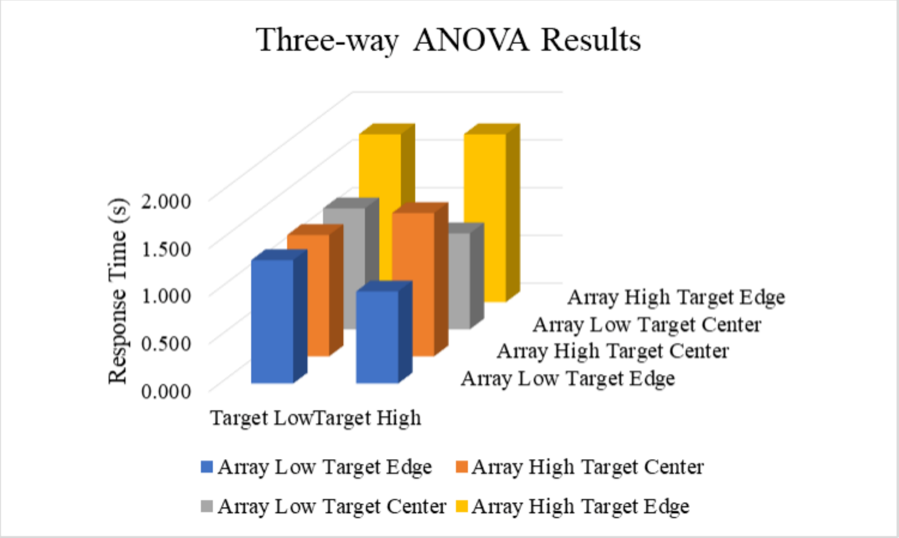


Fig. 21. Three-way interaction between "AR UI Clutter Level", "Target Clutter Level", and "Target AR UI Position".

The four-way interaction between (AR UI Clutter Level)*(Target Clutter Level)*(Target AR UI Position)*(Target Depth Level) implies that the "Target Depth Level" variable is only significant when all other variables are taken into account. This could imply that target depth matters when the all properties of the AR UI are viewed simultaneously. In terms of AR UI design this would mean that visual search performance is a function of all properties simultaneously, and it may be difficult to separate out the effects of each individual variable on visual search time.

6.6.2 Pearson Correlation of Clutter Measures

6.6.2.1 AR UI clutter

All image analysis measures (edge density, feature congestion, and sub band entropy) of AR UI Clutter correlated with visual search time. This result agrees with previous research into image analysis measures and performance of [52], [69], [99], as well as with previous research in AR UIs [125]. Each image analysis measure was positively correlated to visual search time edge density; r(78)=.54, p<.001, feature congestion; r(78)=.54, p<.001, sub-band Entropy; r(78)=.53, p<.001). They are all similar to each other in the level of correlation meaning that the image analysis measures may be redundant to each other. This has implications for future applications as some measures may be easier to implement than others based on an application, so not all may be needed.

6.6.2.2 Target clutter

No image analysis measures (edge density, feature congestion, and sub band entropy) of “Target Clutter” showed significant correlation to visual search time; edge density r(78)=.13, p=.238, feature congestion; r(78)=.07, p=.567, sub-band Entropy; r(78)=-.06, p=.596. This result disagrees with previous studies where target clutter was investigated as a post-hoc variable. This study also involved seven apparent AR UI planes and 3D AR UI objects and targets while previous studies used 2D objects and a maximum of 3 apparent AR UI planes. This could mean that as an AR UI gets more complex, in terms of object representation and AR UI planes, the clutter of a target matters less. It also could be that in controlling for the target clutter variable, the range of target clutter was compressed, leading to a weaker correlation to visual search time.

6.6.2.3 Target position

The variable of “Target Eccentricity” showed a significant positive correlation with visual search time r(78)=.29, p=.010. This finding disagrees with the results of the ANOVA which showed that the “Target AR UI Position” does not have a significant effect on visual search time. However, this result agrees with the results of previous work in 2D displays, [109]–[114], and the results of the previous studies.. An explanation of this could be that our discrete groupings are too large and are obscuring eccentricity effects as there is overlap of eccentricity values between the center and edge conditions of “Target AR UI Position”. The narrow field of view provided by the device also limits interpretation as none of the objects would fall into what would be considered the periphery of the field of view.

Neither “Target Depth” nor “Target Total Distance” showed any significant correlation with visual time. Since target size is held constant and there is no occlusion this implies that the apparent depth of a target does not have an effect on search time.

While there could have been some accommodation-vergence conflicts [137] at holographic projection distances beyond the hardware fixed 2m [138] the lack of significant correlation of visual search time to target depth, as seen in Table 21, implies that these effects were not prevalent. While participants were instructed to remain stationary, they were not precluded from moving, so accidental occlusion would be possible. This result implies that effects of any accidental occlusion were minimal, as it can be assumed that if occlusion was an issue, then there would be an expected significant positive correlation.

6.6.3 Multiple Regression

Using the results, a multiple regression relationship was established between a natural logarithmic transformation of visual search time and measures or AR UI clutter, measures of target clutter, and target eccentricity. A significant regression equation was found (F(9,70)=5.35, p<.001), with an R^2 of 0.407, adjusted R^2 of 0.331. The independent variable coefficients and significance are shown in the following table.

Table 23. Regression Model

Variable	*Coefficient*	*p*
Intercept	-5.017	*p*=.600
Target X Angle	.633	***p*=.008**
Target Y Angle	.384	*p*=.330
Target Z	-.125	*p*=.617
Target ED	2.974	*p*=.389
Target FC	.00297	*p*=.961
Target SE	-0.119	*p*=.089
AR UI ED	-27.948	*p*=.908
AR UI FC	0.612	*p*=.907
AR UI SE	1.285	*p*=.568

An alternative regression strategy used the average of normalized image analysis measures for the AR UI clutter and the target clutter. A significant regression equation was found (F(5,74)=9.07, p<.001), with an $R^2 = .380$, $Adjusted\ R^2 = 0.338$. The independent variable coefficients and significance are shown in the following table.

Table 24. Alternate Regression Model 1

Variable	*Coefficients*	*p*
Intercept	.118	*p*=.312
AR UI Clutter Avg	.165	***p*<.001**

Target Clutter Avg	-.0173	*p*=.702
Target X Angle	.708	***p*=.002**
Target Y Angle	.237	*p*=.535
Target Z	-.042	*p*=.856

As can be seen in the first analysis, while the regression is significant overall, the only significant variable is the target horizontal position. Image analysis measures of clutter for both the AR UI and the target are not significant as well. When the average of normalized image analysis measures of clutter is looked at, however, we find that the AR UI clutter is significant, though the target clutter is still not significant. This could be due to limitations in the study for examining a very limited clutter range. The significance of the target horizontal location but not the target vertical location could also be due to the limitations of the study and equipment of having a small, and tightly packed field of view.

A strategy of only using the most computational efficient image analysis measure of edge density along with target position gives the following. A significant regression equation was found (F(5,74)=8.98, p<.001), with an $R^2 = .378$, Adjusted $R^2 = .335$. The independent variable coefficients and significance are shown in the following table.

Table 25. Alternate Regression Model 2

Variable	***Coefficients***	***p***
Intercept	-.788	***p*<.001**
Target X Angle	.716	***p*=.002**
Target Y Angle	.206	*p*=.588
Target Z	-.030	*p*=.896
AR UI ED	52.359	***p*<.001**
Target ED	.253	*p*=.887

This multiple regression model would be less computationally resource intense to apply and gives similar results to a more complex model.

6.6.4 Discussion Summary

Interpreting the results of the Pearson correlation between search time and image analysis measures for the AR UI clutter and target clutter, the measure that correlates best with visual search time is edge density. Edge density correlates as well as sub-band entropy and feature congestion for the AR UI and performs better than sub-band entropy and feature congestion for target clutter measures.

The results of the target position variables ("Target Eccentricity", "Target Depth", target total distance) show that the shorter visual search times come from objects closer to the center of focus to the user, but at distance of 4m and further.

In practice, both feature congestion and sub-band entropy required more computational time than edge density, which was equal to or better than those measures in terms of significance. Meaning that if a quick, or even real-time analysis of AR UIs was needed, then edge detection could be used alone as a measure of AR UI clutter and a predictor of visual search time. While this study used the Canny edge detection algorithm [139], there are other edge detection algorithms available that may offer even less computational time and greater speed [140], [141]. This is important as it could help in designing dynamic mobile AR UIs [142]. This result could also be integrated into extant dynamic space management algorithm for UIs [143]. It could also be integrated into context based dynamic interfaces as an additional help to performance [144].

Synthesizing the effects of AR UI clutter, target clutter, and target position together show that overall AR UI clutter is a critical factor for visual search times in the conditions tested in this experiment. This result was also confirmed through a multiple regression analysis. "Target Depth" is also a factor, but its effect seems to be influenced by other independent variables more than the overall clutter. "Target Eccentricity" showed low positive correlation to search time, but it was not able to be tested over a larger range of visual angles.

6.7 Conclusions

This work characterizes the relationship between visual search time and the variables of target clutter, target depth, and target eccentricity, as well as further developing the relationship between visual search time and AR UI clutter from [124], [125].

Using the results of this experiment we can develop an initial algorithm for analyzing AR UIs.

$$\begin{aligned}\ln(Search\ Time) &= -5.017 + 0.633(Target\ X\ Angle) + 0.384(Target\ Y\ Angle) \\ &- 0.125(Target\ Z) + 2.974(Target\ ED) + 0.003(Target\ FC) \\ &- 0.119(Target\ SE) - 27.948(Array\ ED) + 0.612(Array\ FC) \\ &+ 1.285(Array\ SE)\end{aligned} \tag{4}$$

While this algorithm lacks accuracy and cannot predict the exact amount of visual search time for a given AR UI, as R^2=.407 (from Section 6.6.3) implies that only around 40% of the variance in search time is explained by the chosen variables, it can still be used to compare AR UIs to each other. For example; if this algorithm was ran on two hypothetical AR UIs, $AR\ UI_1\ and\ AR\ UI_2$ and output the results $AR\ UI_1 = 1.61\ and\ AR\ UI_2 = .69$, then as the lower value, $AR\ UI_2 = .69$ would be associated with shorter visual search times. The value of $AR\ UI_2 = .69$ is not in seconds, but in but in $ln(seconds)$. Taking the inverse of each value would give the expected visual search time in seconds $AR\ UI_1 = 1.61 = e^{1.61} = 5seconds$ and $AR\ UI_2 = .69 = e^{.69} = 2seconds.$

Given that R^2=.407 the most appropriate use of this algorithm would be to score general expected performance through the metric of visual search time instead of expecting it to predict exact visual search time. The current iteration of the algorithm can be used as a comparison tool with the lower the visual clutter score, the better the AR UI, further refinements will allow it to be used as a predictive visual search time tool.

6.8 Future Work and Limitations

This work will be used to improve the algorithm found in Equation (4). an algorithm comprised of (n_x) factors that affect visual search time in AR UIs. The algorithm will output a predicted search time. This can then be used to compare different AR UI configurations to each other, with the

The plan for future studies is to expand on this by moving the study to real-world locations with dynamic backgrounds and a mixture of real and virtual targets. This will build a fuller featured model capable of predicting visual search time for a wider variety of applications and AR UI systems.

General Limitations of this study are detailed in Section 3.4

While the results of this research may not yet be able to accurately predict visual search time based on an AR UI configuration, the results can still compare two different AR UIs and establish which one will result in better user visual search time.

7 Summation

7.1 Summary of Key Findings

7.1.1 Factors That Affect Visual Search Time

7.1.1.1 AR UI clutter

All studies showed that image analysis measures of AR UI clutter were related to visual search time which agrees with results from the literature for non-AR UIs. A summary of the results is shown in the following table.

Table 26. Pearson Correlations of Image Analysis Measures of Clutter to Visual Search Time

	Study 1			**Study 2**			**Study 3**		
	N=90			**N=120**			**N=80**		
Variable	**r**	***p***	**Power**	**r**	***p***	**Power**	**r**	***p***	**Power**
AR UI ED	.25	***p*=.017**	.61	.29	***p*=.002**	.90	.54	***p*<.001**	1.00
AR UI FC	.27	***p*=.012**	.70	.28	***p*=.002**	.87	.54	***p*<.001**	1.00
AR UI SE	.28	***p*=.008**	.75	.27	***p*=.003**	.84	.53	***p*<.001**	1.00

The studies show that AR UI clutter correlates more with visual search time for AR UIs comprised of more planes of apparent depth or for AR UIs comprised of 2D vs 3D objects. In both studies 1 and 2, the AR UI objects are 2D, as opposed to the 3D renderings of study 3. Also study 1 uses an AR UI comprised of a single apparent plane, and the maximum number of apparent AR UI planes in study 2 is 3, while study 3 has nine apparent AR UI planes.

7.1.1.2 Target clutter

Image analysis measures of clutter had various levels of correlation throughout the studies. In both studies 1 and 2, positive correlation was observed while no significant correlations were found for study 3. A summary of the results is shown in the following table.

Table 27. Pearson Correlation of Image Analysis Measures of Target Clutter to Visual

Search Time

	Study 1			**Study 2**			**Study 3**		
	N=90			**N=120**			**N=80**		
Variable	**r**	***p***	**Power**	**r**	**p**	**Power**	**r**	**p**	**Power**
TargetED	.19	***p*=.037**	.39	.35	***p*<.001**	.98	.13	*p*=.238	.22
TargetFC	.25	***p*=.006**	.77	.34	***p*<.001**	.97	.07	*p*=.567	.09
TargetSE	.23	***p*=.010**	.68	.20	***p*=.032**	.46	-.06	*p*=.596	.08

7.1.1.3 Target positions

Across all three studies, target eccentricity correlated with visual search time. For studies 2 and 3, neither target apparent depth nor target total distance were significantly correlated to visual search time. A summary of the results are shown in the following table.

Table 28. Pearson Correlation of Target Position to Visual Search Time

	Study 1			**Study 2**			**Study 3**		
	N=90			**N=120**			**N=80**		
Variable	**r**	***p***	**Power**	**r**	**p**	**Power**	**r**	**p**	**Power**
TargetXAngle	0.10	*p*=.367	.76	0.04	*p*=.652	1.00	0.24	*p*=.145	.14
TargetYAngle	0.04	*p*=.720	1.00	-0.01	*p*=.895	1.00	0.13	*p*=.157	.06
TargetEccentricity	0.20	***p*=.030**	.47	0.25	***p*=.006**	.77	0.29	***p*=.010**	.74
TargetZ				0.04	*p*=.681	1.00	-0.19	*p*=.086	.41
TargetXYZ				0.14	*p*=.139	.05	-0.19	*p*=.088	.40

7.1.1.4 Target type, projected or AR

Whether or not the target was projected or virtual had an effect on visual search time, which was more pronounced if there was a 50%/50% mixture of projected and AR objects in an AR UI. This variable was not further examined as the focus of the research shifted to be more on the AR UI itself and not on external properties.

7.1.2 Efficacy of Image Analysis Measures on Characterizing Visual Search Time

When used to analyze the AR UI, image analysis measures of edge density, feature congestion, and sub-band entropy were shown throughout all the studies to correlate with visual search time. Correlation coefficients were generally similar across all image analysis measures for studies 1 and 2. Study 3 saw an increase in the correlation coefficients, but the image analysis measures were still similar to each other within the study. When used to analyze the target, image analysis measures of edge density, feature congestion, and sub-band entropy correlated with visual search time for studies 1 and 2, but not for study 3.

Overall, the image analysis measures of clutter are viable when used on the AR UI to characterize visual clutter and its correlation to visual search time in several different conditions. The measures show some viability in characterizing the visual clutter of a target and its inherent correlation to visual search time, but it seems to be more condition dependent.

7.2 Discussion of Key Findings

The results across all studies show that clutter affects visual search times in AR, and that image analysis measures of clutter are effective measures of visual clutter for AR. These results are most applicable to the overall clutter of the AR UI and show an increase in correlation as the number of apparent AR UI planes goes from ≤3 to 9 and from 2D to 3D UI objects. Measures of target clutter also correlate to visual search time, but only when the number of apparent AR UI planes is ≤3 and UI objects are 2D. At 9 apparent AR UI planes, target clutter no longer significantly correlates. This could be because the complexity of more AR UI planes and 3D objects has a greater effect than target clutter. This result agrees with measures of AR UI clutter correlating better for these more complex AR UIs meaning that the AR UI complexity is seemingly more important than other factors.

The relationship of target positions to visual search time shows that the most important position factor across all studies is the target eccentricity. The further the target is from the center of the AR UI the more difficult it is to find, which agrees with the results of previous research [109]–[114]. The target apparent depth and target total distance did not significantly affect visual search time except for the case when target apparent depth was discrete (near or far) instead of continuous and the AR UI display was comprised of 9 apparent planes.

7.3 Contributions: Implications for AR UI Design and Assessment

This research holds many implications for both future AR UI design as well as the development of a way to assess AR UIs. A main takeaway is that AR UIs are much more complex than a traditional UI. In a traditional UI there is only one type of target that an individual would be searching for, there is no depth to a target, and there is no depth to the UI itself. AR UIs however have all of those issues.

The results of this research show that while AR UI clutter is an important factor in visual search time, other factors such as display type, target clutter, target eccentricity, target type, and percentage of AR objects in an AR UI all have large effects on visual search time as well. This result is meaningful as these are all variables that can be accounted for in the design of an AR UI, knowing that these are factors allows them to be addressed in the design phase, which helps to streamline the process of AR UI design. The effectiveness of image analysis measures in assessing AR UI clutter and performance through the metric of visual search time also help to streamline the process of AR UI design. Image analysis measures can be run without the need for human assessment and can be automated to run streamlining data collection as well as AR UI assessment throughout the design phase. Furthermore, since the three image analysis measures (edge density, feature congestion, and sub-band entropy) had very similar correlation coefficients to visual search time, not all may be needed in a given situation. This allows flexibility in applying measures as AR UI designers would be able to pick with image analysis technique works most efficiently in a given application.

Using the results, a multiple regression relationship was established between a natural logarithmic transformation of visual search time and; measures or AR UI clutter, measures of target clutter, and measures of target eccentricity. A significant regression equation was found (F(10,149)=17.09, p<.001), with an $R^2 = .534$, $Adjusted\ R^2 = .503$. The independent variable coefficients and significance are shown in the following table.

Table 29. Regression Model 1

Variable	***Coefficient***	***p***
Intercept	.51	*p*=.936
Target X Angle	.76	***p*<.001**
Target Y Angle	.73	***p*=.006**
Target Z	-.15	*p*=.377
Array ED	112.25	*p*=.489
Array SE	1.02	*p*=.500
Array FC	-2.09	*p*=.550
Target ED	-.27	*p*=.908
Target SE	-.10	***p*=.031**
Target FC	.07	*p*=.093

An alternative regression strategy used the average of normalized image analysis measures for the AR UI clutter and the target clutter. A significant regression equation was found (F(6,253)=26.00, p<.001), with an $R^2 = .505$, $Adjusted\ R^2 = .485$. The independent variable coefficients and significance are shown in the following table.

Table 30. Regression Model 2

Variable	***Coefficients***	***p***
Intercept	-.235	***p*=.005**
Target Weight	.003	*p*=.916
Array Weight	.144	***p*<.001**
Target X Angle	.823	***p*<.001**
Target Y Angle	.597	***p*=.024**
Target Z	-.066	*p*=.679

Regression model 1 shows that while the regression is significant overall, the only significant variables are, target horizontal visual angle, and vertical visual angle and target sub-band entropy. Image analysis measures of clutter for the AR UI and feature congestion and edge density image analysis measures for the target are not significant. When the average of normalized image analysis measures of clutter for the AR UI and for the target is looked at, however, we find that the AR UI clutter is significant, though the target clutter is still not significant. This could be due to limitations in the study for examining a very limited clutter range. The continued lack of significance of the target apparent depth agrees with both the ANOVA and Pearson correlation results.

A strategy of only using the most significant variables of display type, averaged AR UI Clutter, Target X Angle, and Target Y Angle gives the following results. A significant regression equation was found (F(4,155)=39.41, p<.000), with $R^2 = .504$, $Adjusted\ R^2 = .491$. The independent variable coefficients and significance are shown in Table 31 following table.

Table 31. Alternate Regression Model 3

Variable	***Coefficients***	***p***
Intercept	-.261	***p*<.001**
AR UI Avg.	.144	***p*<.001**
Target X Angle	.823	***p*<.001**
Target Y Angle	.598	***p*=.022**

This multiple regression model provides the most efficient model utilizing only the significant variables while still providing an adjusted R^2 comparable to the more complex models.

The multiple regression analysis can be converted into an algorithm for comparing AR UIs. The equation outputs a single numeric value that represents the efficacy of a given AR UI with the lower the number the better the lower expected visual search time.

Model with all variables

$$\begin{gathered} Performance = 0.51 + 0.76(Target\ X\ Angle) + 0.73(Target\ Y\ Angle) - 0.15(Target\ Z) \\ + 112.25(AR\ UI\ ED) + 1.02(AR\ UI\ SE) - 2.09(AR\ UI\ FC) \\ - 0.27(Target\ ED) - 0.10(Target\ SE) + 0.07(Target\ FC) \end{gathered} \tag{5}$$

Model with only significant variables

$$\begin{gathered} Performance = -0.261 + 0.144(AR\ UI\ Avg.) + 0.823(Target\ X\ Angle) \\ + 0.598(Target\ Y\ Angle) \end{gathered} \tag{6}$$

While not refined, these algorithms allow the assessment of expected visual search time when searching for a given target in a given AR UI. It is based on measures of clutter for both the AR UI as well as the target object, and on the position of the target object relative to the user. It is applicable for head-worn optical see-through displays. It is important to note that this algorithms' output is not yet meant to be an accurate predictor of visual search time. It is instead meant to be a tool to compare the efficacy of one AR UI to another AR UI. For example, the algorithm will output a single number that is representative of expected user performance (in terms of visual search time) for a given AR UI, but is not the visual search time. To compare two different AR UIs, the algorithm would be ran on each AR UI, and the AR UI which had the lower score, would be expected to have the better user performance.

This algorithm falls between the formative and summative phases of AR UI design. It would be most appropriate to use the algorithm to evaluate the AR UI anytime after an initial AR UI design had been established, up through analyzing extant AR UIs.

As there are several different ways of choosing variables for analyzing the AR UI, it would be possible to choose both a full featured analysis (all variables) for in lab design and analysis, as well as selecting a more computationally "lightweight" algorithm for embedded review of the AR UI for applications such as dynamic AR UI displays.

Taking the results of the studies together provides AR UI designers with both guidelines to use during the design phase of an AR UI as well as an assessment tool to use after an AR UI has been designed to assess its efficacy.

7.4 Limitations

A major limitation in this research was the limited range of objects used. While the object selection allowed the study to remain domain independent, a set of domain dependent objects would allow the research to be more directly applicable and increase the fidelity of the studies. The studies also used a semi structured search task using household objects, which may not be applicable to all forms of AR UI use. The layout of the AR UI was in a grid format which also may not be applicable to other AR UI layouts.

The limited field of view of the HoloLens1 was also a major limitation. As this study used headmounted optical see-through AR, it may not be applicable to non-head-mounted optical seethrough AR, or to AR UI's that expand more into the periphery of the field of view.

The study focused on the measure of visual search time, while forgoing measures of accuracy and perceived difficulty such as the NASA-TLX. This was done as this study was focused on determining upper bound visual search performance without a focus on accuracy, and was focused on occupational instead of consumer use.

The algorithm is focused entirely with the goal of optimizing speed through the measure of visual search time. As such it does not account for issues such as accuracy or user enjoyment.

While the results of this research may not yet be able to accurately predict visual search time based on an AR UI configuration, the results can still compare two different AR UI's and establish which one will result in better user visual search time.

7.5 Future Research Directions

The plan for future work is to first add the variables of static real-world background clutter and to compare head-fixed and world fixed AR UIs. After these variables are accounted for, the AR UI Visual Clutter Score Algorithm will be refined and then will need to go to a validation phase of testing.

After the first round of validation testing the variable of static real-world background clutter will be replaced with dynamic real-world backgrounds. Following the addition of the dynamic realworld background the AR UI will move to a mixture of real-world targets and world-fixed AR targets embedded in the real-world. Once these variables have been added, another validation phase will occur.

This research plan will build an algorithm capable of predicting visual search time for a wide variety of AR UIs and applications. A goal at any point in this process is to embed the most up to date AR UI Visual Clutter Score Algorithm into an AR UI itself so that the UI can dynamically vary itself in order to maintain a given level of visual search time.

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9 Appendix

9.1 Study 1 Tests for Normality

Tests of Normality			
		Kolmogorov-Smirnov	**Shapiro-Wilk**

Condition	Description	Statistic	df	p	Statistic	df	p
1	Array Low_25_Real	0.151	12	.200*	0.931	12	0.386
2	Array Low_25_Virtual	0.165	12	.200*	0.920	12	0.286
3	Array Low_50_Real	0.197	12	.200*	0.871	12	0.068
4	Array Low_50_Virtual	0.378	12	0.000	0.727	12	0.002
5	Array Low_75_Real	0.271	12	0.015	0.841	12	0.028
6	Array Low_75_Virtual	0.139	12	.200*	0.952	12	0.662
7	Array Medium_25_Real	0.158	12	.200*	0.973	12	0.941
8	Array Medium_25_Virtual	0.179	12	.200*	0.904	12	0.178
9	Array Medium_50_Real	0.189	12	.200*	0.912	12	0.227
10	Array Medium_50_Virtual	0.203	12	0.184	0.880	12	0.088
11	Array Medium_75_Real	0.222	12	0.104	0.896	12	0.140
12	Array Medium_75_Virtual	0.196	12	.200*	0.909	12	0.209
13	Array High_25_Real	0.294	12	0.005	0.843	12	0.030
14	Array High_25_Virtual	0.212	12	0.142	0.892	12	0.125
15	Array High_50_Real	0.201	12	0.197	0.908	12	0.202
16	Array High_50_Virtual	0.300	12	0.004	0.820	12	0.016
17	Array High_75_Real	0.227	12	0.090	0.951	12	0.648
18	Array High_75_Virtual	0.220	12	0.114	0.849	12	0.036

9.2 Study 2 Tests for Normality

		Kolmogorov-Smirnov			Shapiro-Wilk		
Condition	**Description**	**Statistic**	**df**	***p***	**Statistic**	**df**	***p***
1	Low_Array2m_Target2m	0.185	12	.200*	0.949	12	0.615
2	Low_Array4m_Target4m	0.141	12	.200*	0.952	12	0.671
3	Low_Array6m_Target6m	0.178	12	.200*	0.953	12	0.687
4	Low_Array2m4m_Target2m	0.198	12	.200*	0.915	12	0.245
5	Low_Array2m4m_Target4m	0.094	12	.200*	0.963	12	0.830
6	Low_Array2m6m_Target2m	0.170	12	.200*	0.938	12	0.477

7	Low_Array2m6m_Target6m	0.206	12	0.170	0.883	12	0.096
8	Low_Array4m6m_Target4m	0.113	12	.200*	0.964	12	0.843
9	Low_Array4m6m_Target6m	0.200	12	.200*	0.912	12	0.227
10	Low_Array2m4m6m_Target2m	0.213	12	0.140	0.956	12	0.729
11	Low_Array2m4m6m_Target4m	0.136	12	.200*	0.961	12	0.799
12	Low_Array2m4m6m_Target6m	0.115	12	.200*	0.964	12	0.841
13	High_Array2m_Target2m	0.239	12	0.057	0.846	12	0.033
14	High_Array4m_Target4m	0.123	12	.200*	0.969	12	0.897
15	High_Array6m_Target6m	0.182	12	.200*	0.936	12	0.450
16	High_Array2m4m_Target2m	0.203	12	0.187	0.901	12	0.165
17	High_Array2m4m_Target4m	0.144	12	.200*	0.934	12	0.426
18	High_Array2m6m_Target2m	0.178	12	.200*	0.953	12	0.676
19	High_Array2m6m_Target6m	0.166	12	.200*	0.966	12	0.860
20	High_Array4m6m_Target4m	0.216	12	0.127	0.877	12	0.079
21	High_Array4m6m_Target6m	0.173	12	.200*	0.889	12	0.115
22	High_Array2m4m6m_Target2m	0.163	12	.200*	0.899	12	0.152
23	High_Array2m4m6m_Target4m	0.148	12	.200*	0.959	12	0.776
24	High_Array2m4m6m_Target6m	0.311	12	0.002	0.672	12	0.000

9.2.1 Study 3 Tests for Normality

		Kolmogorov-Smirnov			**Shapiro-Wilk**		
Condition	**Description**	**Statistic**	**df**	***p***	**Statistic**	**df**	***p***
1	Low_Low_Near_Center	0.160	12	.200*	0.971	12	0.918
2	Low_Low_Near_Edge	0.160	12	.200*	0.958	12	0.757
3	Low_Low_Far_Center	0.157	12	.200*	0.938	12	0.470
4	Low_Low_Far_Edge	0.175	12	.200*	0.936	12	0.446
5	Low_High_Near_Center	0.159	12	.200*	0.949	12	0.620
6	Low_High_Near_Edge	0.144	12	.200*	0.949	12	0.620
7	Low_High_Far_Center	0.173	12	.200*	0.928	12	0.361
8	Low_High_Far_Edge	0.171	12	.200*	0.913	12	0.234

9	High_Low_Near_Center	0.188	12	.200*	0.934	12	0.422
10	High_Low_Near_Edge	0.132	12	.200*	0.947	12	0.587
11	High_Low_Far_Center	0.140	12	.200*	0.915	12	0.249
12	High_Low_Far_Edge	0.131	12	.200*	0.933	12	0.412
13	High_High_Near_Center	0.187	12	.200*	0.924	12	0.318
14	High_High_Near_Edge	0.244	12	0.046	0.856	12	0.044
15	High_High_Far_Center	0.179	12	.200*	0.905	12	0.184
16	High_High_Far_Edge	0.138	12	.200*	0.956	12	0.731

9.3 IRB 9.3.1 Informed

Consent Form

Virginia Polytechnic and State University - Consent to Take Part in a Research Study

Title of Research Study:

Applying Measures of Visual Clutter to the Head Worn Augmented Reality Space

Principal Investigator:

Joseph Gabbard

Supported By:

Grado Department of Industrial and Systems Engineering
Virginia Polytechnic and State University.

Financial Interest Disclosure:

Not Applicable for this study

Key Information about this research study:

The following is a short summary of this study to help you decide whether to be a part of this study. Information that is more detailed is listed later on in this form.

The purpose of this study is to evaluate the effects of visual clutter on a visual search task in augmented reality user interfaces. You will be wearing a Microsoft HoloLens device and you will be performing a visual search task where you will be searching for an object in an array of objects.

We expect that you will be in this research study for approximately an hour.

Primary Risks
Eye Strain - No more than risks than are found in everyday life.
Headache - No more than risks than are found in everyday life.
Discomfort from wearing HoloLens - No more than risks than are found in everyday life.

Why am I being asked to take part in this research study?

We are asking you to take part in this research study because you are over 18 and have eyesight that is at or has been corrected to 20/20.

How many people will be in this study?

We expect about __**12**___ people here will be in this research study.

What should I know about participating in a research study?

- Someone will explain the research study to you.
- Whether or not you take part is up to you.
- You can choose not to take part.
- You can agree to take part and later change your mind.

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Virginia Polytechnic and State University - Consent to Take Part in a Research Study

- Your decision will not be held against you.
- You can ask all the questions you want before you decide.

What happens if I say, "Yes, I want to be in this research"?

- You will arrive at the Cogent Lab in room 530 Whittemore Hall
- You will fill out a brief background survey; age, gender
- You will then receive some brief training on the equipment and to make sure the HoloLens is properly fitted on you and you can clearly see the objects
- You will then participate in a series of trials where you will be asked to find a given object in a field of objects.
- Total Time should be less then 1 hour
- An investigator will be in the room with you to advance to the next trial and to record your answers.

Will being in this study help me in any way?

Not Applicable

Is there any way being in this study could be bad for me?

Primary Risks
Eye Strain - No more than risks than are found in everyday life.
Headache - No more than risks than are found in everyday life.
Discomfort from wearing HoloLens - No more than risks than are found in everyday life.

What happens if I do not want to be in this research?

Participation in research is voluntary. You can decide to participate or not to participate.

What happens if I say "Yes", but I change my mind later?

You can leave the research at any time and it will not be held against you.

If data has already been collected you will be asked if you are ok with us keeping the data for later processing if it turns out we can use the partial data. If you would like all of the collected information to be deleted, then it will be deleted from the data sets.

What happens to the information collected for the research?

Efforts will be made to limit the use and disclosure of your personal information, including research study records, to people who have a need to review this information. We cannot promise complete secrecy. Organizations that may inspect and copy your information include the IRB and other representatives of this institution

If identifiers are removed from your identifiable private information or identifiable samples that are collected during this research, that information or those samples could be used for future research studies or distributed to another investigator for future research studies without your additional informed consent.

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De-identified data that is collected may be shared outside of the study team. Certain sponsors now require this de-identified data to be made available files to the research community, as do a growing number of journals in a variety of disciplines.

Data Sharing

De-identified data from this study may be shared with the research community at large to advance science and health. We will remove or code any personal information that could identify you before files are shared with other researchers to ensure that, by current scientific standards and known methods, no one will be able to identify you from the information we share. Despite these measures, we cannot guarantee anonymity of your personal data.

Can I be removed from the research without giving my OK?

Not Applicable

What else do I need to know?

Not Applicable

Compensation

Not Applicable

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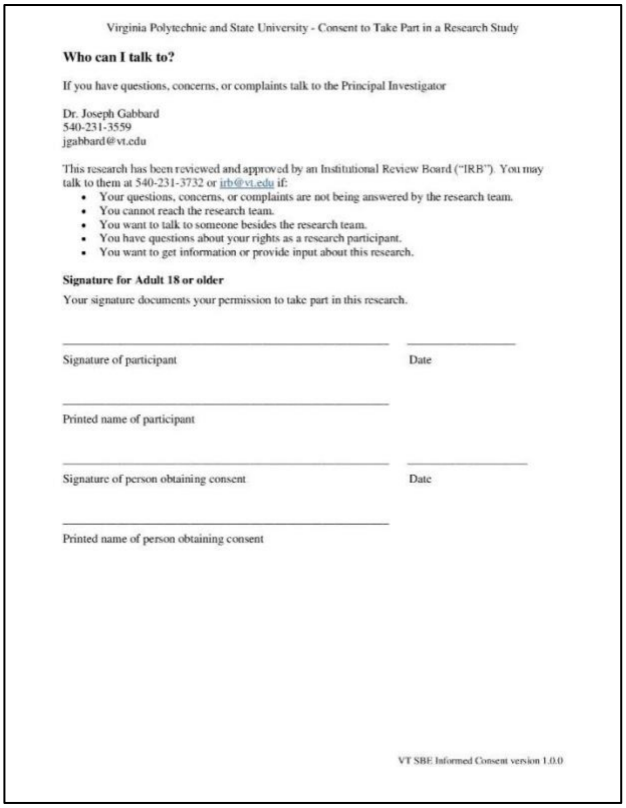

Virginia Polytechnic and State University - Consent to Take Part in a Research Study

Who can I talk to?

If you have questions, concerns, or complaints talk to the Principal Investigator

Dr. Joseph Gabbard
540-231-3559
jgabbard@vt.edu

This research has been reviewed and approved by an Institutional Review Board ("IRB"). You may talk to them at 540-231-3732 or irb@vt.edu if:

- Your questions, concerns, or complaints are not being answered by the research team.
- You cannot reach the research team.
- You want to talk to someone besides the research team.
- You have questions about your rights as a research participant.
- You want to get information or provide input about this research.

Signature for Adult 18 or older

Your signature documents your permission to take part in this research.

______________________________________ ____________

Signature of participant Date

____

Printed name of participant

______________________________________ ____________

Signature of person obtaining consent Date

____

Printed name of person obtaining consent

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