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Detecting bombs in hold baggage: 3D imaging is better than 2D imaging when image quality is the same

Marius Latscha [a,b,*], Sarah Merks [b], Jürgen Sauer [c], Adrian Schwaninger [a,b]

[a] University of Applied Sciences and Arts Northwestern Switzerland, School of Applied Psychology, Institute Humans in Complex Systems, Olten, Switzerland
[b] Center for Adaptive Security Research and Applications (CASRA), Zurich, Switzerland
[c] University of Fribourg, Department of Psychology, Fribourg, Switzerland

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ABSTRACT

Three-dimensional (3D) imaging is increasingly utilized in hold baggage screening (HBS) at airports. It enables screeners to rotate images and view cross-sectional layers of the bag (slicing). Previous studies on multi-target search in cabin baggage screening indicate that novices benefit from 3D-rotatable images when image quality is the same in 2D and 3D. We investigated the effects of 3D imaging for professional screeners in HBS, where the screening task is to detect bombs in pre-alarmed bags flagged by automated explosives detection systems. In our study, 51 professional screeners completed a highly realistic HBS task involving two levels of bag complexity in 2D and 3D imaging conditions with the same image quality. We found that 3D imaging resulted in higher detection performance in terms of hit rate and sensitivity (d' and d_a, two sensitivity measures of signal detection theory). Although better bomb detection was accompanied by increased response times, the practical implication of our results is that the transition to 3D HBS substantially enhances human-machine system performance in terms of both effectiveness and efficiency.

1. Introduction

Airports employ various security measures to prevent prohibited items from entering aircraft (Cordova, 2022). In cabin baggage screening (CBS), X-ray images of carry-on luggage are visually inspected by airport security officers (screeners), who search for guns, knives, explosives, and other prohibited items. Hold baggage, however, is stored in the hold of the aircraft, which is not accessible to passengers during flights. Therefore, hold baggage screening (HBS) only targets bombs, technically called improvised explosive devices (IEDs). These consist of four components connected to each other often using wires: an explosive, a detonator, a power source, and a triggering device (Turner, 1994; Wells and Bradley, 2012). HBS uses multiple layers for IED detection. In the first layer, each bag is scanned using two-dimensional (2D) X-ray and/or three-dimensional (3D) computed tomography (CT) machines equipped with automated explosives detection systems (EDS; Caygill et al., 2012; Harding, 2004; Singh and Singh, 2003; Wells and Bradley, 2012). These EDS automatically highlight areas in images of bags that might contain explosive material. In the second layer, the images of the alarmed bags are sent to screeners, who visually inspect the images to decide whether they contain an IED. When screeners suspect an IED, additional measures are initiated (e.g., re-screening, explosives trace detection, and manual search; Hättenschwiler et al., 2019a). In Europe, 3D imaging in HBS has been mandatory for all airports since 2024 (European Commission, 2021). It offers interactive imaging functions such as 3D image rotation and slicing. These functions enable screeners to examine bags from multiple angles and view cross-sectional slices. In other regions of the world, 2D systems are still used for HBS, because transitioning to 3D imaging is costly, requiring significant investments in new baggage screening equipment, and because there are concerns that intensive and specific 3D HBS training is needed before screeners can work effectively and efficiently with 3D imaging systems. In our study, we investigated whether professional HBS screeners benefit from 3D imaging functions compared to 2D imaging when image quality is the same, and whether these benefits are more pronounced for complex images.

1.1. 2D versus 3D imaging

Visual search for prohibited items in X-ray images of passenger

* Corresponding author. University of Applied Sciences and Arts Northwestern Switzerland, School of Applied Psychology, Institute Humans in Complex Systems, Olten, Switzerland.
E-mail address: marius.latscha@casra.ch (M. Latscha).

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baggage is a demanding task involving attention, perception, memory and decision-making (Hättenschwiler et al., 2019b; for reviews, see Biggs et al., 2018; Biggs and Mitroff, 2014; Donnelly et al., 2019). Traditionally, HBS relied on 2D X-ray imaging, which generates images based on the absorption of X-rays (Caygill et al., 2012; Cordova, 2022; Harding, 2004; Singh and Singh, 2003). Multi-view 2D systems typically use dual-view (DV) technology, presenting bags from two angles (e.g., top-down and side view), which mitigates the limitations of single-view imaging (von Bastian et al., 2008). The 2D DV approach is particularly beneficial for addressing challenges in single-view images due to superposition (overlapping objects), unusual viewpoints, and high bag complexity due to opacity and clutter, all of which impact visual inspection performance (Bolfing et al., 2008; Bravo and Farid, 2004, 2006; Godwin et al., 2017; Schwaninger et al., 2005a, 2005b).While 2D DV imaging increases inspection time, it improves target detection compared to 2D single-view imaging (von Bastian et al., 2008). Enhanced detection performance was also found when multiple views of a bag were presented as an image sequence (Mendes et al., 2013).

Beyond 3D imaging, 3D CT technology is increasingly utilized in HBS at airports. Compared to 2D DV X-ray, 3D systems offer enhanced EDS capabilities, reduced false alarms and improved screening efficiency (Cordova, 2022; Mouton and Breckon, 2015; Oftring, 2015; Velayudhan et al., 2022; Wells and Bradley, 2012). Moreover, 3D imaging provides interactive functions such as image rotation and slicing. Rotation allows the screener to virtually rotate images 360° along any axis. Slicing enables the screener to slice through the image by displaying cross-sectional layers of the bag. Both functions, rotation and slicing, may facilitate target detection. However, a notable drawback is that 3D systems sometimes have lower image quality than 2D systems used at airports (Velayudhan et al., 2022). Image quality is measured using a standard test piece to assess single wire resolution, useful penetration, spatial resolution, material penetration, and material discrimination (see Hättenschwiler et al., 2019a for details). Only a few studies have investigated the impact of 3D imaging on baggage screening performance. Several years ago, Hättenschwiler et al. (2019a) tested professional screeners with realistic simulators of a 2D DV HBS system and a 3D HBS system widely used at that time. While response times (RT) were higher with 3D, sensitivity (d') remained similar across imaging conditions. The authors argued that the lack of positive effects observed for 3D over 2D imaging was likely due to the lower image quality in the 3D condition offsetting the benefits of rotation and slicing. However, newer 3D systems provide better image quality than the system used in their study, reaching the same image quality as some 2D systems currently used at airports. Counteracting effects of lower image quality on enhanced visual inspection performance with 3D were supported by two recent online studies on CBS with screening novices. They found better performance for 3D in experiments using the same image quality for 2D DV and 3D conditions (Godwin et al., 2024; Parker et al., 2022). In the study of Parker et al. (2022), the authors used a 3D condition with interactive video recordings of cabin baggage rotating 360° along two axes. They found higher sensitivity (d') in the 3D condition compared to a 2D DV condition with static images. Better target detection for 3D than 2D DV in CBS was also reported by Godwin et al. (2024), who conducted a study with fully rotatable images in the 3D condition. They found higher accuracy and increased RT for 3D compared to 2D DV. However, both studies focused on novices and multi-target search in CBS (for a review see Mitroff et al., 2015), which differs from HBS. In CBS, the targets include guns, knives, IEDs, and other prohibited items, whereas HBS focuses on detecting IEDs (Merks et al., 2018). Moreover, research suggests that results found with novices do not always apply to visual inspection of professional screeners (e.g., Chavaillaz et al., 2019; Hättenschwiler et al., 2019b; Swann et al., 2024; Wagner et al., 2024). Experience and training are crucial for achieving high detection performance (Halbherr et al., 2013; Koller et al., 2008; McCarley et al., 2004; Schuster et al., 2013). Experienced screeners also use different search strategies than inexperienced screeners (Swann et al., 2024) and interact differently with automated decision support systems (Chavaillaz et al., 2019).

In summary, previous research suggests that the benefits of 3D imaging in HBS can be offset by limited image quality (Hättenschwiler et al., 2019a). However, newer 3D systems have image quality comparable to that of some 2D systems currently used at airports. Studies on CBS indicate that novices benefit from rotatable 3D images over static 2D DV images when image quality is the same. For professional screeners in HBS, however, the benefits of 3D over 2D imaging under equal image quality conditions remain unclear. Addressing this gap was the primary motivation for our study.

1.2. Measures of screener performance

Detection performance in baggage screening can be measured in terms of hit rate (HR; percent correct responses on target-present images) and false alarm rate (FAR; percent incorrect responses on target-absent images). Both measures are important, because high HR is crucial for security, and high FAR can jeopardize checkpoint efficiency (Dorton and Liu, 2016; Sterchi and Schwaninger, 2015). In real-world baggage screening, the frequency of targets (target prevalence) is about 2%, because airports use threat image projection (TIP), which projects pre-recorded target X-ray images into the stream of visually inspected images (Hofer and Schwaninger, 2005). Most studies on visual search, however, apply a significantly higher target prevalence of 50% to ensure high statistical power. Target prevalence is known to affect participants' tendency to decide that a target is present (criterion shift or response bias; Green and Swets, 1966; Hautus et al., 2021; Wolfe et al., 2007; Wolfe and Van Wert, 2010). When targets appear more frequently, participants adopt a more liberal decision criterion, which increases both HR and FAR (Biggs and Mitroff, 2014; Buser et al., 2019; Menneer et al., 2010; Mitroff and Biggs, 2014; Sterchi et al., 2019; Wolfe et al., 2007; Wolfe and Van Wert, 2010). It is therefore recommended not to rely solely on HR and FAR in studies with high target prevalence but to also calculate sensitivity, which is independent of target prevalence (Green and Swets, 1966; Hautus et al., 2021; Sterchi et al., 2019). Signal detection theory (SDT; Green and Swets, 1966) provides the sensitivity index d', a measure of sensitivity widely used in research on visual inspection performance in baggage screening (e.g., Godwin et al., 2010b; Huegli et al., 2020; Menneer et al., 2010; Muhl-Richardson et al., 2021; Rusconi et al., 2015; Schwaninger et al., 2010; Yu and Wu, 2015). SDT posits that each decision on whether a target is present is based on two subjective evidence distributions (noise and signal-plus-noise). Assuming that these distributions are normal and of equal variance, d' is defined as the distance between the means of these distributions. However, several studies showed that the equal variance assumption does not always hold for visual search in baggage screening (Godwin et al., 2010a; Sterchi et al., 2019; Van Wert et al., 2009; Wolfe et al., 2007; Wolfe and Van Wert, 2010). Alternative measures, such as d_a (Simpson and Fitter, 1973), which account for unequal variance between evidence distributions, should therefore be considered. Following the recommendations of Sterchi et al. (2019), HR, FAR, d', and d_a with a slope parameter (standard deviation ratio) of 0.5 should be used to assess visual inspection performance in baggage screening tasks. In addition, target-present and target-absent RT can provide insights into visual inspection processes. RT are also relevant from a practical standpoint, as they directly impact baggage throughput.

1.3. Present study

The present study examined the performance of 3D imaging compared to 2D DV imaging in HBS. We extended previous research by using images of a newer 3D HBS system than that used in Hättenschwiler et al. (2019a), providing comparable image quality to some of the 2D HBS systems currently used at airports. Addressing limitations of previous research and ensuring high ecological validity, we compared the performance of professional HBS screeners in a realistic screening task using authentic 3D CT images and an interface replicating typical 3D imaging functions. We used the same image quality in both the 2D and 3D conditions. Additionally, bags with varying levels of complexity were used to assess whether 3D imaging benefits are more pronounced for complex bags. To provide a comprehensive comparison of 2D and 3D imaging effects in HBS, we examined the performance measures d', d_a, HR, FAR, and RT.

2. Method

2.1. Participants

Fifty-four professional hold baggage screeners were recruited from an international airport to participate in a simulated HBS task conducted at facilities near the airport. A priori power analysis using G*Power 3.1 (Erdfelder et al., 2009) indicated that this sample size was more than sufficient to detect medium to large effects using a mixed analysis of variance (ANOVA; at least 38 participants are needed to detect medium to large effects with an alpha error probability of 0.05 and a statistical power of 0.85). All screeners were trained and certified according to European aviation security regulations (European Commission, 2015). Participants had a mean age of 48 years ($SD = 9.4$), an average of 8.5 years of work experience with 2D baggage screening ($SD = 5.6$), and no prior experience with 3D baggage screening. They were randomly assigned to either the 2D or the 3D imaging condition. All screeners provided informed consent and were free to withdraw from the experiment at any time. Three screeners did not complete the experiment, resulting in a final sample of 51 screeners (31 females, 20 males), with 24 in the 2D condition (14 females, 10 males) and 27 in the 3D condition (17 females, 10 males).

2.2. Design

We used a 2x2 mixed design with imaging condition (2D, 3D) as a between-subjects factor and bag complexity (low, high) as a within-subjects factor. The dependent variables were d', d_a, HR, FAR, target-present RT, and target-absent RT.

2.3. Apparatus and stimuli

Stimuli were presented using X-Ray Tutor Version 4 (XRT4; CASRA - Center for Adaptive Security Research and Applications, 2024. https://www.casra.ch/.), a highly realistic simulator software for computer-based training and testing of screeners. XRT4 features an interface that is similar to those of 2D and 3D imaging systems used at airports. The task included 256 images of hold baggage. Half of them (n = 128) contained an IED (target-present images), while the other half (n = 128) did not contain any prohibited items (target-absent images). Both image sets (target-present and target-absent) contained an equal number of low- and high-complexity bag images. We used real images of hold baggage recorded with a 3D HBS system with higher image quality than that used in Hättenschwiler et al. (2019a). Bag complexity was rated by three aviation security experts from the Center for Adaptive Security Research and Applications (CASRA - Center for Adaptive Security Research and Applications, 2024. https://www.casra.ch/.). The experts had several years of experience working as screeners and in stimuli creation for computer-based training and testing. Bag complexity was defined as: "How difficult a bag is to visually inspect depending on its content. Bag complexity increases with greater amount of clutter, number of items, and metallic objects." To ensure a shared understanding of bag complexity levels, the three experts first reviewed all images collectively. They then independently rated each image on a 10-point scale (1 = very low complexity, 10 = very high complexity). To ensure consistency in bag complexity classification, images with discrepancies of more than three rating points between experts were excluded. From the remaining images, 64 low-complexity images (mean rating ≤ 5) and 64 high-complexity images (mean rating >5) were selected as target-absent images. The experts created target present images by developing 64 distinct IEDs using a variety of detonators, explosive materials, triggers, and power sources connected to each other. These IEDs were then 3D recorded and digitally merged into the target-absent images using image merging algorithms of CASRA. Each IED was used twice, once in a low-complexity and once in a high-complexity bag image. Because in HBS only images that contain an EDS alarm are sent to screeners for visual inspection (see introduction), a red frame was placed around the IEDs in the target-present images. In the target-absent images, the frames were placed around materials and items that sometimes induce false alarms in HBS (e.g., certain chocolate, cheese, cosmetics, fruits, shoes). The same set of 3D CT recordings was used for both the 2D and 3D conditions to ensure the same image quality. In the 3D condition, the images were rotatable in three dimensions and sliceable (see supplementary material for a video demonstration of the 3D condition, including rotation and slicing). In the 2D condition, the images were presented in DV from two fixed angles, differing by 90° (side view and top view), rotation and slicing were not possible. The initial views in the 3D condition were used as the side and top view in the 2D condition. Fig. 1 shows the XRT4 simulator interface used in the 2D and the 3D conditions with images of low bag complexity (a) and high bag complexity (b). The screening task was conducted on 19″ TFT monitors, with images covering approximately two-thirds of the screen. Participants were seated approximately 60 cm from the screen.

2.4. Procedure

After providing informed consent, participants received instructions on how to use the simulator to visually inspect the 2D DV images (screeners in the 2D group) or the 3D CT images (screeners in the 3D group). Participants were instructed to visually inspect each image and decide whether it contains an IED. They were told that, as in real-life operations, the EDS marks areas that could be explosive material. As the participants were certified screeners, they knew that an IED consists of four components (explosive material, detonator, triggering device, and power source) that are connected to each other, with varying distances between them depending on the IED type. Participants were informed about the number of images and the target prevalence. They were instructed to work quietly, focused, and as if they were working at the airport. They were told to decide for each bag image as quickly and accurately as possible whether it contains an IED. Each decision had to be indicated by clicking either an OK button (indicating that no target is present) or NOK button (indicating that a target is present) on the simulator interface (see Fig. 1). Images were displayed one after the other and up to 90 s before disappearing. If the time limit for an image was exceeded, screeners still had to indicate their decision before the next image was displayed. After receiving instructions, participants completed a practice block of 10 trials (5 target-absent and 5 target-present images in random order) to familiarize themselves with the task and the interface. Participants received feedback on each response during practice trials. After the practice block, the actual test started without feedback on responses, containing a total of 256 trials, divided into two blocks of equal size (128 images each). Target prevalence was 50% in each block. Order of blocks was counterbalanced across participants, and the order of images within each block was randomized for each participant. Participants were instructed to have a break of at least 10 min after completing the first block. The completion of the experiment took 71 min on average ($SD = 10$ min). While European regulations stipulate that screeners have a break every 20 min of continuous visual inspection of X-Ray images (European Commission, 2015), recent studies suggest that no major decline in screener performance is expected over the continuous screening durations used in our experiment (Buser et al., 2019, 2023; Latscha et al., 2024). Up to four participants

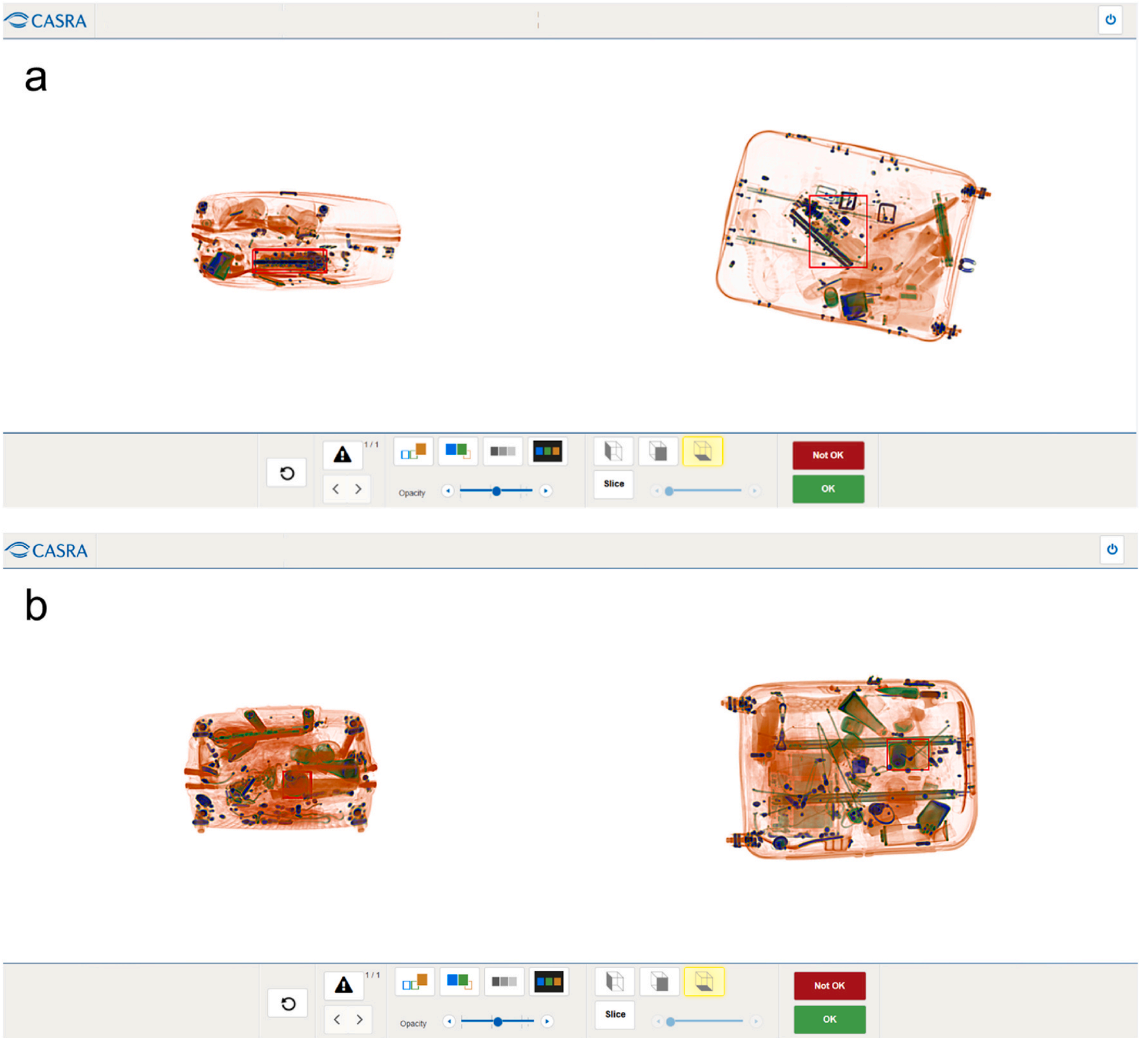

Fig. 1. Interface of the XRT4 simulator with images of low bag complexity (a) and high bag complexity (b). In the 3D condition, the image on the left could be rotated in three dimensions, while the image on the right could be sliced (see supplementary material for a video demonstration of the 3D condition, including rotation and slicing). In the 2D condition, the images appeared as static dual views. Suspicious areas where explosive material might be present were highlighted with a red frame in both imaging conditions.

completed the task in the same room, reflecting typical HBS scenarios (Kuhn, 2017). Screeners worked individually, quietly, and under supervision.

2.5. Measures

The dependent variables were defined as follows, whereby hits are correct responses on target-present trials, misses are incorrect responses on target-present trials, correct rejections are correct responses on target-absent trials, and false alarms are incorrect responses on target-absent trials. z is the inverse of the cumulative distribution function of the standard normal distribution, and s (in our case set to 0.5) is the ratio between the standard deviations of the target-absent (noise) and target-present (signal-plus-noise) distribution (Hautus et al., 2021; Sterchi et al., 2019).

$$\text{HR} = \frac{hits}{hits + misses}$$

$$\text{FAR} = \frac{false\ alarms}{false\ alarms + correct\ rejections}$$

$$\text{d'} = z(HR) - z(FAR)$$

$$\text{d}_\text{a} = \sqrt{\frac{2}{1+s^2}} \times [z(HR) - sz(FAR)]$$

Target-present RT = Mean time from image onset to the responses on target-present trials

Target-absent RT = Mean time from image onset to the responses on target-absent trials.

2.6. Analyses

To rule out significant sample differences between the 2D and 3D groups, we computed independent-samples t-tests on the variables age and tenure. Screener performance was examined by computing two-way mixed ANOVAs for each of the above-mentioned measures with imaging condition (2D, 3D) as between-subjects factor and bag complexity (low, high) as within-subjects factor. We did not analyse differences in response tendency (criterion) because it is not clear how to interpret this measure across different levels of sensitivity (Hautus et al., 2021). Post hoc comparisons were conducted using Holm-Bonferroni corrections (Holm, 1979). All analyses were conducted using R Statistical Software (v4.3.1; R Core Team, 2023).

3. Results

There was no statistically significant difference in age between participants in the 2D and 3D conditions (2D: $M = 48.9$, $SD = 8.7$; 3D: $M = 47.4$, $SD = 10.3$), $t(49) = 0.58$, $p = .566$, and no significant difference in tenure (2D: $M = 9.7$, $SD = 6.3$; 3D: $M = 7.4$, $SD = 4.5$), $t(49) = 1.50$, $p = .140$. Table 1 shows the means (M) and standard deviations (SD) for the performance measures by imaging condition (2D, 3D) and bag complexity (low, high). Table 2 provides the F values, p values, and effect sizes from the two-way mixed ANOVAs for each dependent variable.

3.1. Sensitivity

Fig. 2 shows the means and 95% confidence intervals (error bars) for the sensitivity measures d' and d_a by imaging condition (2D, 3D) and bag complexity (low, high).

For both sensitivity measures (d' and d_a), there were significant main effects of imaging condition, with higher sensitivity in the 3D condition (d': $M = 2.26$, $SD = 0.70$; d_a: $M = 2.05$, $SD = 0.62$) than in the 2D condition (d': $M = 1.62$, $SD = 0.36$; d_a: $M = 1.29$, $SD = 0.39$). Moreover, there was a significant main effect of bag complexity for both sensitivity measures, with higher sensitivity for low (d': $M = 2.16$, $SD = 0.64$; d_a: $M = 1.93$, $SD = 0.61$) than high bag complexity (d': $M = 1.76$, $SD = 0.66$; d_a: $M = 1.45$, $SD = 0.70$). There was no significant interaction between imaging condition and bag complexity for either d' or d_a.

Table 1
Performance by imaging condition (2D, 3D) and bag complexity (low, high).

Variable	Imaging Condition	Bag Complexity Low		Bag Complexity High	
		M	*SD*	*M*	SD
d'	2D	1.82	0.36	1.43	0.44
	3D	2.45	0.69	2.05	0.69
d_a	2D	1.57	0.37	1.04	0.52
	3D	2.25	0.60	1.82	0.65
HR	2D	0.73	0.12	0.57	0.14
	3D	0.86	0.08	0.78	0.12
FAR	2D	0.14	0.11	0.12	0.09
	3D	0.11	0.10	0.13	0.10
target-present RT (s)	2D	9.10	2.40	11.05	2.87
	3D	9.92	2.88	12.17	2.83
target-absent RT (s)	2D	9.40	2.94	10.51	3.37
	3D	10.66	2.52	12.67	2.91

Note. M = mean, SD = standard deviation.

3.2. Hit rate and false alarm rate

For HR, there were significant main effects of imaging condition (2D: $M = 0.65$, $SD = 0.12$; 3D: $M = 0.82$, $SD = 0.98$) and bag complexity (low: $M = 0.79$, $SD = 0.12$; high: $M = 0.68$, $SD = 0.17$), along with a significant interaction between these variables. Post hoc tests revealed that HR was significantly higher in the 3D condition compared to the 2D condition for both low-complexity ($p < .001$) and high-complexity bags ($p < .001$), with a larger difference observed for high-complexity bags. Additionally, HR was significantly higher for low than high bag complexity in both the 2D ($p < .001$) and 3D conditions ($p < .001$), though the difference was smaller in the 3D condition. For FAR, there were no significant main effects of imaging condition (2D: $M = 0.13$, $SD = 0.10$; 3D: $M = 0.12$, $SD = 0.10$) and bag complexity (low: $M = 0.12$, $SD = 0.09$; high: $M = 0.13$, $SD = 0.11$), and no significant interaction between these variables.

3.3. Response times

Fig. 3 shows the means and 95% confidence intervals (error bars) for HR, FAR, target-present RT, and target-absent RT by imaging condition (2D, 3D) and bag complexity (low, high).

We observed slightly higher target-present RT with 3D ($M = 11.04$, $SD = 2.79$) than 2D ($M = 10.07$, $SD = 2.57$), although the main effect of imaging condition was not significant. There was a significant main effect of bag complexity (low: $M = 9.54$, $SD = 2.68$; high: $M = 11.64$, $SD = 2.88$), with higher target-present RT for high-complexity bags. There was no significant interaction between imaging condition and bag complexity for target-present RT. For target-absent RT, there were significant main effects of imaging condition (2D: $M = 9.96$, $SD = 3.10$; 3D: $M = 11.66$, $SD = 2.59$) and bag complexity (low: $M = 10.07$, $SD = 2.77$;

Table 2
F value, p value and effect size (η_p^2) for the main effects of imaging condition (2D, 3D) and bag complexity (low, high), and their interaction.

Variable	Imaging Condition			Bag Complexity			Interaction		
	F	p	η_p^2	F	p	η_p^2	F	p	η_p^2
HR	**28.84**	**< .001**	**.370**	**127.60**	**< .001**	**.723**	**17.90**	**< .001**	**.267**
FAR	0.18	.677	.004	0.05	.826	.001	3.91	.054	.074
d'	**16.85**	**<.001**	**.256**	**63.32**	**<.001**	**.564**	0.01	.955	.000
d_a	**25.26**	**<.001**	**.340**	**95.01**	**<.001**	**.660**	1.04	.312	.021
target-present RT	1.65	.205	.033	**144.92**	**<.001**	**.747**	0.69	.409	.014
target-absent RT	**4.59**	**.037**	**.086**	**55.46**	**<.001**	**.531**	**4.58**	**.037**	**.085**

Note. Degrees of freedom were identical across all analyses: $F(1, 49)$. Statistically significant effects ($p < .05$) are presented in bold.

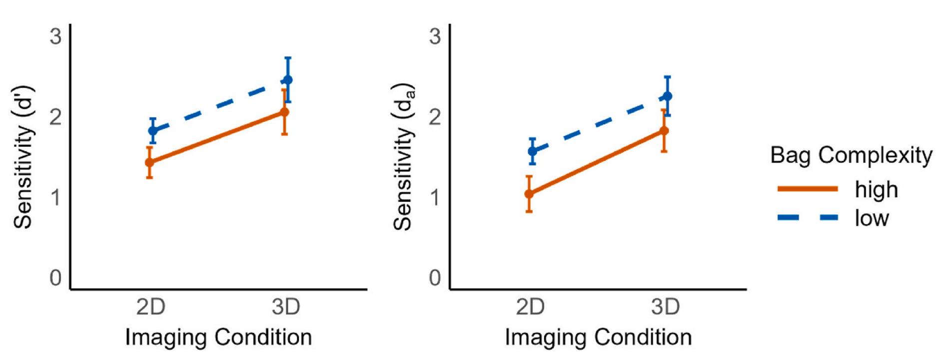

Fig. 2. Sensitivity indices d' (left) and d_a (right) by imaging condition (2D, 3D) and bag complexity (low, high). Error bars represent 95% confidence intervals.

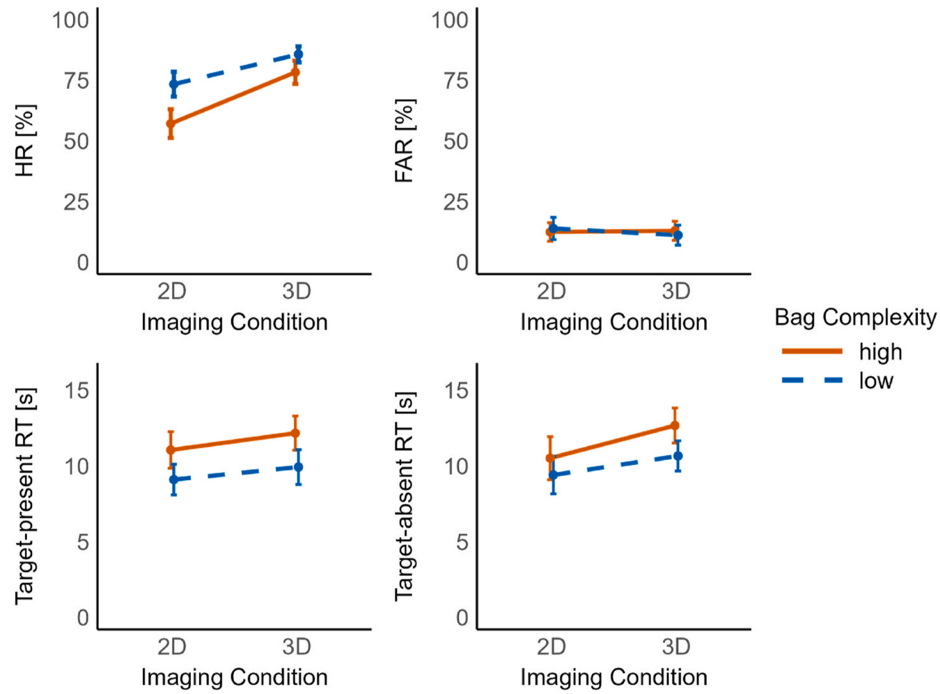

Fig. 3. Hit rate (HR), false alarm rate (FAR), target-present RT, and target-absent RT by imaging condition (2D, 3D) and bag complexity (low, high). Error bars represent 95% confidence intervals.

high: $M = 11.65$, $SD = 3.29$), as well as a significant interaction between these variables. Post hoc tests revealed that target-absent RT was significantly higher with 3D compared to 2D for high bag complexity ($p = .018$). For low bag complexity, the difference in target-absent RT between 2D and 3D was not significant ($p = .106$). Target-absent RT was significantly higher for high bag complexity than for low bag complexity in both the 2D ($p < .001$) and 3D conditions ($p < .001$).

4. Discussion

In this study, we tested professional HBS screeners using highly realistic simulators and stimuli in 2D and 3D imaging conditions with the same image quality. Both conditions utilized the same set of images, which varied in bag complexity (low, high). To assess the impact of imaging technology on performance, we analysed sensitivity indices (d' and d_a), hit rate (HR), false alarm rate (FAR), and response times (target-present and target-absent RT) as dependent variables.

4.1. Sensitivity

We found higher sensitivity in the 3D condition compared to the 2D condition. This is consistent with the assumption that rotation and slicing in 3D imaging support a more comprehensive visual inspection. In our study, image quality was the same across the 2D and 3D conditions, representing a key difference from previous research conducted by Hättenschwiler et al. (2019a). In their study, the authors found similar sensitivity for 2D and 3D. They argued that the absence of a difference in sensitivity found in their study might be due to the poorer image quality in the 3D compared to the 2D condition, which may have offset the potential benefits of rotation and slicing. In our study, we used 3D images from an HBS system with higher image quality than the one used in Hättenschwiler et al. (2019a), and we compared screeners' performance under 3D and 2D imaging conditions with the same image quality. We observed better detection performance in terms of sensitivity in the 3D condition compared to the 2D condition, indicating that screeners benefit from 3D imaging functions when image quality is the same. Notably, the positive effect on detection performance observed in our study was robust in the sense that we observed higher sensitivity for 3D regardless of the sensitivity measure used (d' or d_a). Two recent online studies that compared 2D and 3D imaging with the same image quality found similar results for CBS with novices: Parker et al. (2022) found higher sensitivity in terms of d' when they presented bag recordings as interactive video sequences with bags rotating around two axes, compared to static 2D DV images. Godwin et al. (2024) did not report sensitivity indices but found higher response accuracies with 3D rotatable bag images compared to 2D DV images. Our study shows that screeners in HBS also benefit from the use of 3D imaging functions. Furthermore, these functions appear to be advantageous even for screeners with limited 3D experience or 3D specific training.

Regarding effects of bag complexity, we found that screeners showed higher sensitivity for images of low-complexity bags, regardless of the imaging condition. This finding aligns with prior research showing that high bag complexity impairs the detection of prohibited items in visual inspection (Bolfing et al., 2008; Schwaninger et al., 2005a, 2005b). While these earlier studies focused on 2D images, our results indicate that the impact of bag complexity also applies for the visual inspection of 3D images. Furthermore, our findings suggest that bag complexity is still relevant when suspicious areas that might contain explosive material (which is one of the components of an IED) are highlighted by the EDS.

4.2. Hit rate and false alarm rate

HR was higher in the 3D condition than in the 2D condition, indicating that screeners are better at detecting IEDs in target-present images when they can rotate and slice the images compared to when they inspect static 2D views. As explained in the introduction, IEDs consist of explosive material, a detonator, a power source, and a triggering device connected to each other often using wires (Turner, 1994; Wells and Bradley, 2012). Most likely, the 3D imaging functions facilitated identifying these IED components. We also found higher HR for low-complexity bags in both imaging conditions. In contrast to sensitivity, where no statistically significant interaction was found between imaging condition and bag complexity, we did observe a significant interaction for HR: the increase in HR between the 2D and the 3D condition was more pronounced for images of high bag complexity. This indicates that for bags with high levels of opacity and clutter, which are difficult to inspect with 2D imaging (Bolfing et al., 2008; Schwaninger et al., 2005b), 3D imaging functions are even more advantageous. We did not observe any significant effects for FAR, which suggests that there was no shift in the screeners' decision criterion. From a practical standpoint, this is favorable, because an increase in FAR would reduce HBS efficiency (Hättenschwiler et al., 2019a). Bag complexity did not impact FAR in either the 2D or 3D condition. Previous research involving a CBS multi-target search task found lower FAR for 2D than for 3D (Godwin et al., 2024). Further research could investigate whether effects of 3D imaging on FAR are more pronounced in CBS, where screeners have to search for guns, knives, IEDs, and other prohibited items, than in HBS, where the targets are only IEDs.

4.3. Response times

RT was higher in the 3D than in the 2D condition, most likely because using rotation and slicing required screeners to invest additional time. This finding aligns with previous research indicating that 3D imaging comes at the cost of higher RT (Godwin et al., 2024; Hättenschwiler et al., 2019a). However, in our study, post hoc tests revealed that the difference in RT between imaging conditions was statistically significant only for target-absent images of high-complexity bags. For target-present RT, we found no statistically significant difference between 2D and 3D. This means that a potential speed-accuracy trade-off was limited to target-absent images of high-complexity bags: a significant increase in detection performance was accompanied by small costs in RT. Previous studies found larger RT differences between 2D and 3D imaging conditions (Godwin et al., 2024; Hättenschwiler et al., 2019a). One possible explanation is that the search component in the task used by Godwin et al. (2024) was more dominant compared to our HBS task, possibly leaving more room for effects on search duration in their study. Regarding bag complexity effects, we found that both target-present RT and target-absent RT increased for high-complexity bags compared to low-complexity ones. This suggests that bags with high levels of opacity and clutter prompt screeners to spend more time evaluating the suspicious areas.

4.4. Practical implications

We found that 3D imaging, using images of a newer 3D HBS system with better image quality than the one tested by Hättenschwiler et al. (2019a), had clear advantages over 2D imaging with the same image quality, including increased sensitivity and higher HR. Moreover, the increase in HR was more pronounced for complex bags. Notably, we observed these positive effects even though the HBS screeners in our study had extensive experience with 2D imaging, no prior experience with 3D imaging, and only 10 practice trials with 3D imaging before the main test. 3D-specific computer-based and on-the-job training, as well as hands-on experience with 3D HBS, might further enhance its beneficial effects. Our findings suggest that the transition from 2D to 3D imaging systems is a meaningful and effective advancement in HBS, leading to improved detection and enhanced security. However, better detection with 3D imaging was accompanied by an increase in target-absent RT. Notably, target-absent RT is particularly relevant in practice, as most images sent to visual inspection in HBS do not contain a threat. Nevertheless, this increase in target-absent RT does not compromise the overall superiority of 3D HBS over 2D HBS in terms of efficiency. On the contrary, even with larger RT differences, as observed in Hättenschwiler et al. (2019a), 3D HBS outperforms 2D HBS in overall human-machine system performance regarding efficiency (i.e., baggage throughput). This is because 3D HBS systems not only achieve higher HR but also much lower FAR than 2D HBS systems (Oftring, 2015; Velayudhan et al., 2022). The lower FAR significantly improves throughput because fewer images of alarmed bags are sent to screeners for visual inspection.

4.5. Limitations and further research

To achieve high statistical power for assessing differences in detection performance, the target prevalence in our study was higher than in real-world HBS, where it is typically around 2% due to TIP (Hofer and Schwaninger, 2005). As noted in the introduction, target prevalence influences HR and FAR through a criterion shift (Green and Swets, 1966; Hautus et al., 2021; Wolfe et al., 2007; Wolfe and Van Wert, 2010). We therefore calculated sensitivity, which is independent of target prevalence (Green and Swets, 1966; Hautus et al., 2021; Sterchi et al., 2019). Further research could examine HR and FAR using TIP data to compare 2D and 3D HBS under operational conditions with low target prevalence. Another limitation of our study is that the 3D imaging condition did not allow us to separate the effects of rotation and slicing. A recent study found that sensitivity increased when a 3D imaging condition was followed by a 2D slice view in an online experiment (Muhl-Richardson et al., 2025). Future studies could further examine the effects of rotation and slicing separately to better understand their individual contributions to screener performance in HBS. Additionally, future studies could use eye tracking and assess subjective perceptions to gain further insights into cognitive processes, usability, and user experience. Furthermore, we found benefits of 3D imaging compared to 2D imaging even though the screeners had extensive experience with 2D and no previous experience with 3D imaging. Further research could examine whether the benefits of 3D imaging are even larger when screeners gain more 3D imaging experience. Finally, it should be noted that the benefits of 3D imaging over 2D imaging may depend on other factors, such as airport-specific operational environments, machine types, training protocols, and equipment configurations. Future research could explore how such factors impact the benefits of 3D HBS.

5. Conclusion

The results of our study indicate that the visual inspection of hold baggage benefits from 3D imaging functions (rotation and slicing), compared to 2D imaging with the same image quality. The 3D imaging functions appear to be particularly beneficial when bag complexity is high. Notably, the positive effects were found for professional HBS screeners who had no prior experience with 3D imaging. However, better IED detection with 3D came at some cost regarding RT.

CRediT authorship contribution statement

Marius Latscha: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Sarah Merks:** Investigation, Conceptualization. **Jürgen Sauer:** Writing – review & editing, Funding acquisition. **Adrian Schwaninger:** Writing – review & editing, Supervision, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

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

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Appendix A. Supplementary data

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