The Impact of an Educational Video on Efficacy Beliefs towards Algorithm Bias in Organisational and Individual-use Algorithms

Dissertation submitted as a requirement for the degree of BSc (Hons) in Applied Psychology, Dun Laoghaire Institute of Art, Design & Technology, 2026

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Warmest regards,

Amreeta Leddy

Word count: 4992

Declaration

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Abstract (198 words):

Algorithmic bias is when users receive unequal outcomes when using an algorithm. This can include functional aspects of algorithmic bias which allow users to filter content to their preference, but also problematic bias e.g. unequal outcomes when users are underrepresented in training data. This study investigated whether an educational video could impact efficacy beliefs towards algorithmic bias in organisational and individual use algorithms. Individual use algorithms are those physically used by individuals e.g. facial recognition algorithm for password protection on devices. Organisational algorithms are those used by organisations e.g. a cv checking algorithm that selects candidates for interview. A factorial 2x2 between-within groups quasi-experimental design was employed. There was a total of 80 participants included in this study, 30 male, 45 female, and 5 gender diverse. The results demonstrated that the participants who watched the educational video had lower efficacy beliefs towards algorithm bias than those who did not. Participants had significantly lower efficacy beliefs towards algorithmic bias in organisational algorithms. The theoretical implications suggest increasing understanding might not always increase efficacy beliefs, regarding a discriminatory system. This study had strong theoretical foundations, but the convenience sampling and quasi-experimental design led to an unrepresentative sample and low ecological validity.

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1. Literature review (*1861 words*)

1.1 Introduction

As algorithms become ubiquitous in daily life, it becomes increasingly important to be efficacious in dealing with the technical problems they might present. Considering algorithms are designed by humans and powered by human data, it is unsurprising that they reflect cognitive and societal biases (Johnson, 2021). A study conducted by Buolamwini and Gebru (2018) revealed that facial recognition algorithms, for example, from Microsoft, struggled to recognise faces with darker skin. This was due to a skewness of training data, which over-represented lighter skinned faces. As a result, the error rate for darker skinned faces was 12.9% compared to 0.7% for lighter skinned faces. This bias is known as algorithmic bias, where an algorithm produces unequal outcomes for users.

Most psychological literature presents algorithmic bias in a negative light, whereas broader discussions in philosophy explore the nuance and scope of algorithmic bias (Chen et al., 2025; Petzel & Sowerby, 2025; Das & London, 2017). From a social psychology lens, AI bias emerges from human data, and as a result perpetuates existing societal implicit biases (Chen et al., 2025; Petzel & Sowerby, 2025). Chen et al. (2025) and Petzel and Sowerby (2025) explore whether participants perceive algorithmic racial and gender bias within algorithm training data and outputs. Algorithmic bias is framed as minorities being underrepresented in the development of these technologies, which results in inequal adoption and user outcomes. This is an aspect explored by Das and London (2017), but the authors argue for a more comprehensive approach to defining algorithmic bias. From a philosophical lens, bias is neutral as it can function positively or negatively. They highlight algorithmic biases which are technical and functional, along with those which are problematic. In fact, Overbye-Thompson and Rice (2025) highlight that exerting bias (e.g. reporting content) to prevent harmful/biased content from showing up on a user's social media feed is a potential workaround.

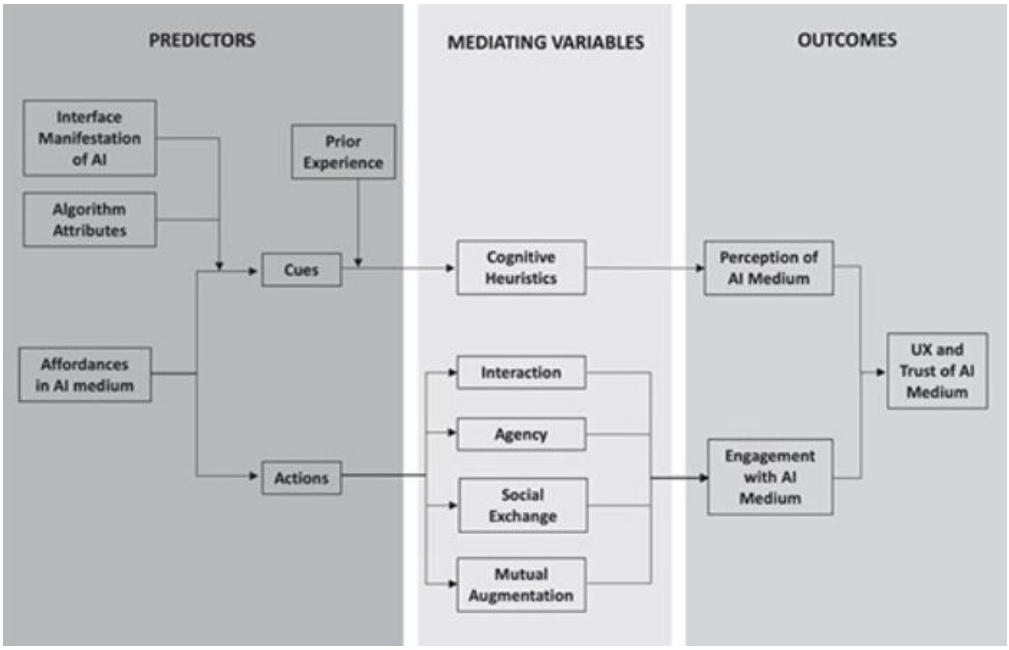
A common thread in the literature conceptualising Algorithmic bias, is the importance of context (Starke et al., 2022). Overbye-Thomspon et al. (2025) highlight two discrete domains of algorithmic bias emerge from the literature: organisational and individual use algorithmic bias. Organisational algorithms, are those used by organisations on individuals. Hiring bias from organisational algorithms is a well-studied form of algorithmic bias (Starke et al., 2022). A study by Ghasemaghaei (2026) explored that people's trust is harmed when algorithm attributes conflict with the ethos of an organisation. Individual use algorithms are those directly employed by users. Within individual use algorithms, search engines have been found to produce biased autosuggestions containing stereotypical beliefs (Graham, 2023).

Prior experience with algorithms is highlighted within Sundar's Human-AI Interactive Theory of Interactive Media Effects (HAII TIME). Along with efficacy beliefs as explored by Overbye-Thompson et al. (2025) these are relevant factors which are neglected in the research surrounding Algorithmic bias. Kohler and Dietrich (2021) reflect that educational videos are a universal tool to increase a user's knowledge. Educational videos have not yet been used in the context of algorithmic bias; thus, the current study will explore whether an educational video will impact the participants efficacy beliefs towards algorithmic bias in organisational and individual-use algorithms.

1.2 The Human-AI Interaction Theory of Interactive Media Effects

According to Sundar's (2020) HAII TIME theory there are two major routes of human-AI interaction, this can be seen below in figure 1. There is the cue route which is based on perceptual cues from the interface, which trigger thought patterns or cognitive heuristics, shaping a user's perception and overall trust of an AI medium. Sundar (2020) suggests that prior experience determine the cognitive heuristics which are unlocked by the interface cues.

Figure 1. Displaying the HAII TIME theory by Sundar (2020)



Sundar (2020) also theorises an action path which addresses the user's interaction with the system, based on the technical attributes (affordances) of the system. Engagement with the system is characterised by interaction, decision-making (Agency), and social exchange or mutual augmentation which shape the medium and the user experience and trust.

Chen et al. (2025) use the HAII TIME to justify the snapshot training data the present to participants by stating it is a visual cue which could trigger cognitive heuristics, and thus perception of bias. Contrastingly, Overbye-Thompson et al. (2025) use the Risk Perception and Attitudes (RPA) framework by Rimal and Real (2003) to examine the efficacy beliefs and

risk perceptions of participants to Algorithmic bias. Which might not be an entirely relevant theoretical framework, given algorithmic bias is not a clearly defined risk (Das & London, 2017).

Efficacy beliefs are not explicitly included in Sundar's (2020) theory. Efficacy beliefs could be categorised as cognitive heuristics, considering they are an aspect of social cognitive theory by Bandura (1986). However, they are theoretically regarded as a foundation for behaviour and thus actions (Bandura, 1986). Overall, efficacy beliefs are likely relevant to both the cue route and the action route.

When applying algorithmic bias workarounds to the HAII TIME theory, Overbye-Thompson and Rice (2025) suggest that the user requires prior knowledge of algorithmic bias to pick up on perceptible cues that indicate bias. They suggest, to successfully complete coping strategies towards algorithmic bias, users must have efficacy to engage with the system. Most psychological studies surrounding algorithmic bias focus on perception or trust rather than efficacy beliefs (Chen et al., 2025; Petzel & Sowerby, 2025; Gutiérrez-Santuiste et al., 2025).

1.3 Algorithmic bias in psychological research

Chen et al. (2025) explored whether laypersons noticed algorithm bias in an emotion-labelling algorithm with higher level of darker faces displaying negative emotions in its training data. Users were shown a snapshot of the training data before they were asked whether the systems were biased. Overall, participants believed both representative and unrepresentative systems were equally biased. According to Sundar's (2020) theory, the participants might not have had prior experience to trigger cognitive heuristics required to distinguish between unbiased and biased training data.

Petzel and Sowerby (2025) conducted an experiment on Participants from the U.S. to measure if trustworthiness and behavioural intentions would be diminished after being shown an interaction with Chat GPT generating inequal pay based on race. Compared to White participants, Black participants had significantly lower trustworthiness when viewing a racially biased interaction. However, after controlling for experience using AI, the

differences were reduced to an insignificant level. This further suggests that prior experience is an important factor in Human-AI interaction (Sundar, 2020).

Gutiérrez-Santuiste et al. (2025) examined whether pre-university students in Spain perceived algorithmic bias across social dimensions. The students were presented with a survey after attending an exhibition on artificial intelligence. Overall, male students had a higher perception of bias across gender and ethnicity. Considering the exhibition was a once-off event, the replicability of this study is low.

The research above, explores the perception of algorithmic bias with a unidimensional approach, without the nuance of the concept (Das & London, 2017). Algorithmic bias is contextualised as discrimination perpetuated by algorithms. The researchers do not contextualise the bias or acknowledge the functional aspects, which could explain the differences between the findings.

As Sundar (2020) suggests, prior experience shapes cognitive heuristics and thus the perception of an AI medium. This is explored within the study Petzel and Sowerby (2025) and moderates the perception of algorithmic bias. Perhaps also by Gutiérrez-Santuiste et al. (2025) as the students gained experience due to the exhibition. The interactivity of algorithms makes it relevant to explore cognitive aspects relating to the formation of behaviour, specifically, efficacy beliefs.

Like Sundar (2020), Bandura (1986) also acknowledges the importance of prior knowledge in the formation of efficacy beliefs. Researching the perception of algorithmic bias might not reveal a solution for when users encounter it and must engage in efficacious techniques. When exploring the psychological implications of algorithmic bias, efficacy beliefs are a relevant avenue (Overbye-Thompson et al., 2025).

1.4 Efficacy Beliefs

Bandura (1986) defines efficacy beliefs as self-belief or confidence to achieve a desired result. Bandura (1986) explains efficacy beliefs are judgements of one's ability to complete a set of tasks, whereas outcome expectations are a judgement of what outcomes emerge

from the completion of the tasks. These beliefs involve an understanding of the organisation and execution required to complete the task; thus, some prior experience or knowledge is required. This intersects with Sundar's (2020) HAII TIME theory which suggests that prior experience shapes cognitive heuristics which form the perception of an AI medium.

Bandura (1986) also highlights that discriminatory systems might distance outcome expectations from self-efficacy judgements. In discriminatory systems, outcomes might not be associated with a successful performance. If two people perform successfully, they could receive inequal outcomes due to social bias.

In the context of algorithmic bias Bandura's (1986) theory suggests that prior experience is required for efficacious techniques. Furthermore, user's efficacy beliefs towards algorithmic bias might be fragmented from their outcome expectations, because they may face inequal outcomes regardless of their technical skills.

1.4.1 Efficacy beliefs towards algorithm bias

The results from a mixed methods study by Overbye-Thompson et al. (2025) displayed differences in the efficacy beliefs users had towards algorithmic bias in individual and organisational algorithms. Overbye-Thompson et al. (2025) adapted the Generalised Self-Efficacy (GSE) scale by Schwarzer and Jerusalem (1995) for the purposes of exploring efficacy beliefs towards algorithmic bias. Users had lower efficacy beliefs towards organisational algorithms. In Sundar's (2020) HAII TIME theory action path, the importance of agency, interaction, social exchange, and mutual augmentation are highlighted. An algorithm designed for organisational use, e.g. a cv checking algorithm selecting a candidate for interview, might lack these aspects. Perhaps these missing attributes from the action path, adversely affects the user's efficacy.

As Bandura (1986) and Sundar (2020) suggest, prior experience forms efficacious techniques and cognitive heuristics surrounding the perception of an AI medium, however, Overbye-Thompson et al. (2025) does not address this factor. The researchers justify their sampling by stating that undergraduate students are algorithmically aware, however, they neglect the aspect of prior experience in their research design. Although theoretically prior

experience plays a role in efficacy beliefs towards algorithmic bias, this has not been explored in the literature.

1.4.2 Educational Video and Efficacy Beliefs

Kohler and Dietrich (2021) highlight that educational videos are a useful tool for teaching scientific concepts. In fact, Hilsman and Dodson (2025) found that a micro-learning video increased nurses' efficacy beliefs to critique nursing research. Lee et al., (2024) found that an educational video improved pain efficacy beliefs in a cohort of orthopaedic patients. Overall, educational videos are cost effective and widely accessible educational tool (Lee et al., 2024).

1.5 The Current Study

Contrastingly to prior psychological research on this topic, the current study does not explore participants' perception of algorithmic bias as a concrete risk (Chen et al., 2025; Petzel & Sowerby, 2025). The current study aims to fill a gap in the literature by exploring the impact of prior experience, via an educational video, on the efficacy beliefs of participants towards algorithmic bias within organisational and individual-use algorithms. Thus, acknowledging the interactivity and nuance of algorithmic bias.

1.5.1 Research Question and Hypotheses

The research question and hypotheses are as follows:

Research Question: Will an educational video impact efficacy beliefs towards algorithm bias within organisational and individual use algorithms?

H_1: There will be a significant difference of the participants efficacy beliefs towards algorithm bias based on whether they watch the educational video or not.

H_2: There will be a significant difference of the participants efficacy beliefs towards algorithm bias based on algorithm type (organisational/individual use).

H_3: There will be a significant interaction between the educational video and algorithm type.

2. Methods (778 words)

2.1 Design

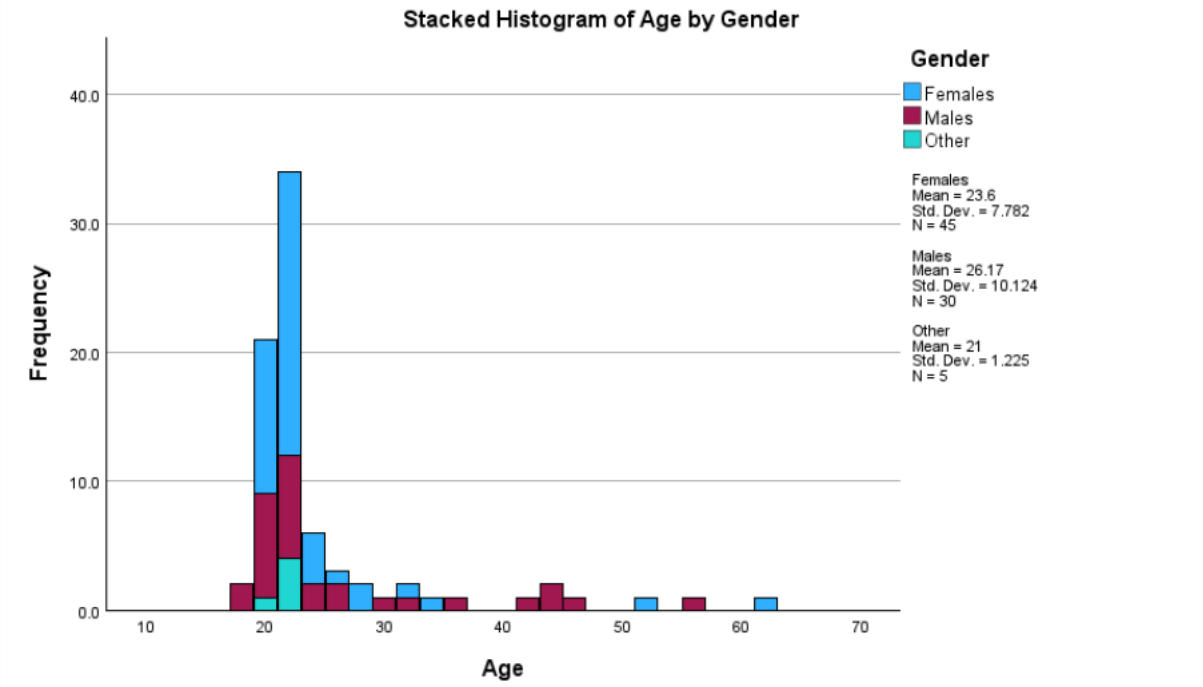
This study utilised a 2x2 groups factorial quasi-experimental between-within design. This study aimed to measure the impact of an educational video on participants' efficacy beliefs towards algorithm bias in individual and organisational algorithms. Individual use algorithms are those physically used by individuals e.g. facial recognition algorithm for password protection on devices. Organisational algorithms are those used by organisations e.g. a cv checking algorithm that selects candidates for interview. Thus, the independent variables were algorithm type (organisational and individual use) and the presence of the educational video.

This design was appropriate for the purposes of the convenience and accessibility to the participants. The questionnaire took an average time of 5 minutes 13 seconds. Statistical testing was conducted on IBM SPSS including descriptive and inferential analyses. A two-way between-within ANOVA was conducted to test H1, H2, and H3.

2.2 Participants

To calculate the sample size a G*Power priori power analysis was conducted (see Appendix A.). With a medium effect size (f=.25), power of .80, and alpha level of .05, the result indicated that 36 participants were required. Overbye-Thompson et al. (2025) limited their study to an undergraduate participant pool. However, this study aimed to target a sample of participants across ages, thus oversampled to 89 participants in total. There were 6 participants excluded due to incomplete responses, and 3 participants who withdrew their participation. The final number of participants was 80.

Figure 2. A stacked histogram displaying the age distribution of participants and gender.



The participants were recruited via convenience sampling at Dun Laoghaire Institute of Art, Design, and Technology (IADT). There were 45 (56.3%) participants who identified as female, 30 (37.5%) as male, and 5 (6.3%) who were gender diverse. Participants ranged from 18 to 61 years old. Most of the participants were aged 22 and younger (71.4%), the age and gender distribution of participants can be seen in *figure 2*.

2.3 Materials

2.3.1 Efficacy Beliefs: Organisational algorithms

A ten-item survey questionnaire was employed from Overbye-Thompson et al. (2025), measuring efficacy beliefs towards algorithm bias in organisational algorithms. This questionnaire was adapted from the GSE scale by Schwarzer and Jerusalem (1995). Example items can be seen in Appendix B. The scale uses a five-point Likert scale from (1) Not at all true to (5) Exactly true. There was high reliability α=.942.

2.3.2 Efficacy Beliefs: Individual use algorithms

A ten-item survey questionnaire was employed from Overbye-Thompson, et al. 2025, measuring efficacy beliefs towards algorithm bias in individual-use algorithms. This questionnaire was adapted from the GSE scale by Schwarzer and Jerusalem (1995). Example items can be seen in Appendix C. The metric uses a five-point Likert scale from (1) Not at all true to (5) Exactly true. The items had high reliability α=.935.

2.3.3 Educational Micro video

An educational video was selected from the University of California Los Angeles (UCLA) Institute for Technology, Law, and Policy YouTube page titled 'AI & Bias- So What's the solution?' (Brannon, et al., 2022). The video is 4 minutes and 49 seconds long, outlining examples of Algorithmic Bias and relevant solutions (Appendix D.). The video is from a series titled 'Demystifying AI' exploring how equitable AI systems can be designed in an accessible format (Brannon et al., 2022).

2.4 Ethics

This study was approved by the Dun Laoghaire Technological Psychological Ethics Committee (DTPEC) at IADT prior to the pilot study (see Appendix E). It follows the code of ethics from The Psychological Society of Ireland (2025), specifically informed consent and freedom of consent. According to the American Psychological Association (2017) ethical guidelines this study also aimed to incorporate bias-free, gender neutral, inclusive language, and avoid stereotyping.

2.5 Pilot study

Following ethical approval, participants (N=9) were provided one of two forms. Survey A contained the educational micro video and Survey B had no video. Both forms contained the questionnaires on efficacy beliefs towards algorithm bias in organisational and individual-use algorithms. The pilot testing revealed that there were issues in the branching of the form. Participants of the pilot study also found that the questionnaire descriptions were confusing, specifically when distinguishing individual and organisational-use algorithms. These issues were considered. Specifically, the questionnaire descriptions were expanded, to include a more detailed description of individual and organisational algorithms. These descriptions were included in plain language, with accompanying images.

2.6 Procedure

One of two online surveys were distributed to participants via QR code on Microsoft Forms. Participants were provided with an information sheet (Appendix F.), then asked for their consent (Appendix G.), and demographic information, specifically their age and gender (Appendix H.). Survey A instructed participants to watch the educational micro video in a quiet room with headphones. Survey B contained no link to a video, only the questionnaire. A branching question ensured that participants were exposed to the questionnaires on efficacy beliefs towards algorithm bias in organisational and individual-use algorithms in a randomised order (Appendix I.). Participants were then debriefed and thanked for their time (Appendix J.).

3. Results (512 words)

Quantitative analysis was conducted on IBM SPSS to test all three hypotheses. Descriptive statistics were conducted to find the sample size (N), average, and standard deviation of efficacy beliefs towards algorithm bias in organisational or individual-use algorithms for each condition. Preliminary testing was conducted to ensure that all the assumptions were met. Followed by inferential analysis which was conducted via a Two-Way between-within groups ANOVA. No post-hoc testing was required as the independent variables only had two levels each.

3.1 Descriptives

Table 1. Displaying the average Efficacy beliefs towards Algorithm Bias in Organisational or Individual use Algorithms for participants who watched the educational video or not.

Descriptive Statistics

	Condition	Mean	Std. Deviation	N
Efficacy Beliefs: Organisational Algorithms	Video	28.55	8.682	42
	No Video	32.89	9.647	38
	Total	30.61	9.353	80
Efficacy Beliefs: Individual use Algorithms	Video	30.26	8.676	42
	No Video	34.34	8.138	38
	Total	32.20	8.619	80

There was a total of 42 participants who were in the educational video condition, and 38 participants who did not see the video. The average efficacy beliefs towards algorithm bias for those who watched the video was 28.55 (SD=8.68) towards organisational, and 30.26 (SD=8.68) for individual-use algorithms. For those who did not see the video, the mean efficacy beliefs towards algorithm bias was 32.89 (SD=9.65) for organisational. The highest average was 34.34 (SD=8.14) for participants who did not watch the video towards

algorithm bias in individual-use algorithms. Detailed tables of descriptives can be found in Appendix K.

3.2 Assumptions

Tests of Normality

Table 2. Displaying the results of the Kolmogorov Smirnov test for Normality

Tests of Normality

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Efficacy Beliefs: Organisational Algorithms	.067	80	.200*	.983	80	.372
Efficacy Beliefs: Individual use Algorithms	.061	80	.200*	.981	80	.275

*. This is a lower bound of the true significance.

a. Lilliefors Significance Correction

The assumption of normality was met, as seen in the *Table 2*. above, all groups had a p value of .200. The assumption of equality of covariance was accepted, Box's M (3) =1.698, p=.648. The assumption of homogeneity of variances was accepted, Levene statistic (1,78) = .389, p=.535 for participants' efficacy beliefs towards Organisational use algorithms in the video and no video condition. For individual-use algorithms, Levene statistic (1,78) =.172, p=.679.

The assumption of sphericity was violated, as there were only two measurements, thus the Greenhouse-Geisser adaptation is applied below. The SPSS outputs for the assumptions can be found in A

Appendix L.

3.3 Inferential statistics

A two way Between-Within groups ANOVA was conducted to test H_1, H_2, and H_3.

H_1: There will be a significant difference between participants of the participants efficacy beliefs towards algorithm bias based on whether they watch the educational video.

H_1 was accepted as the ANOVA revealed that those who watched the video had significantly lower efficacy beliefs towards algorithm bias, $F(1, 78) = 5.154$, $p = .026$. The mean difference based on marginal means was 4.214, and the effect size was also medium eta squared= .062. This is displayed below in *figure 3*. and *4*.

Figure 3. Line graph displaying Efficacy Beliefs towards Algorithm bias within Organizational Algorithms between conditions.

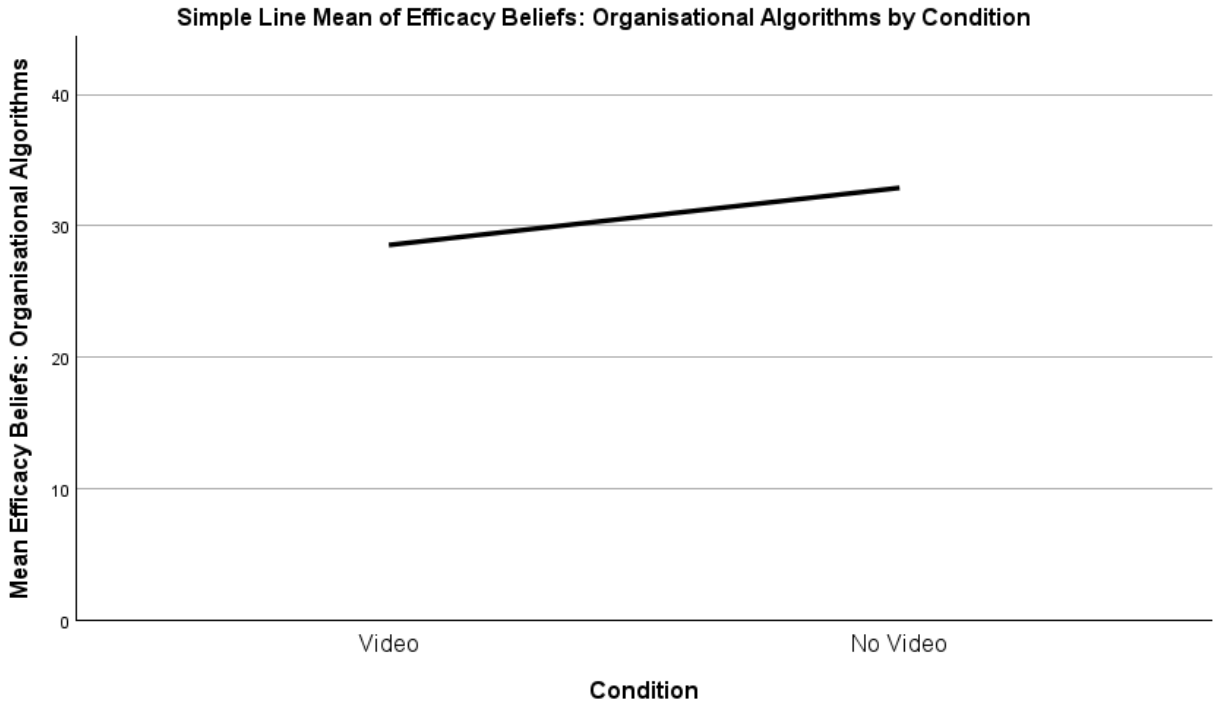
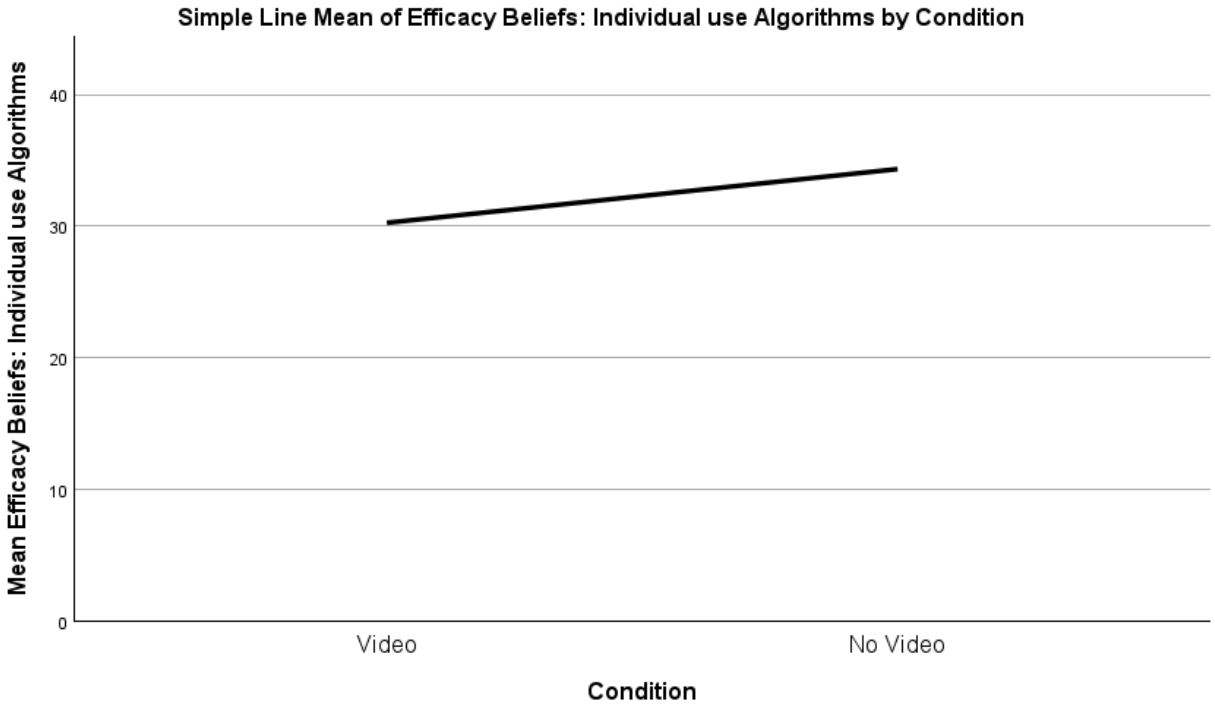


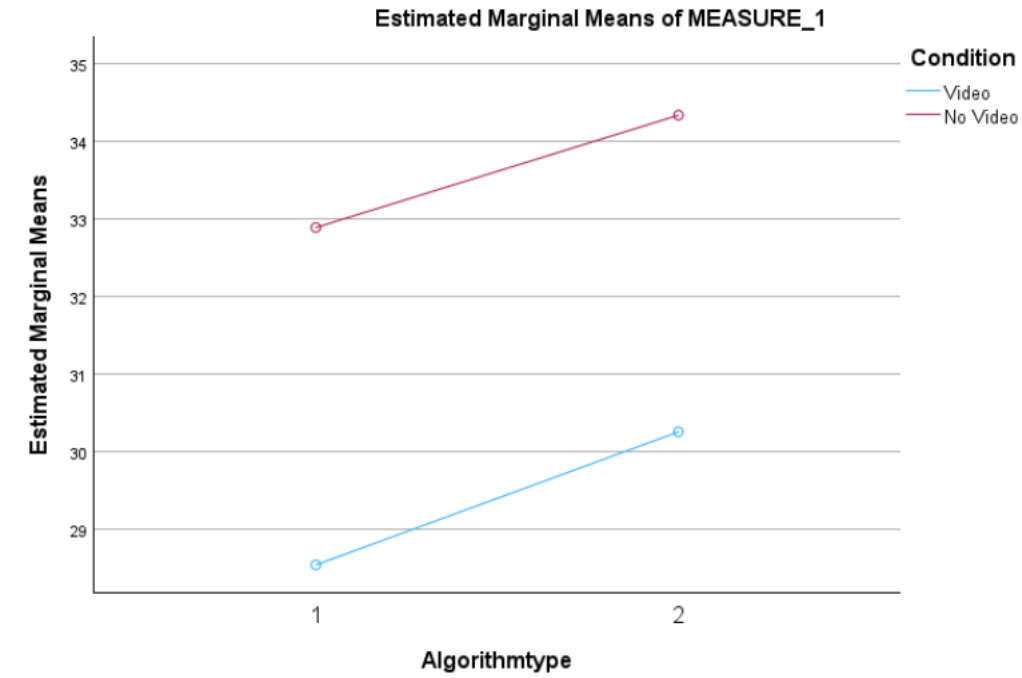
Figure 4. Line graph displaying Efficacy Beliefs towards Algorithm bias within Individual-use Algorithms between conditions.



H_2: There will be a significant difference of the participants efficacy beliefs towards algorithm bias based on algorithm type (organisational/individual use).

The Greenhouse-Geisser adaptation was applied. H_2 was accepted, as the Efficacy beliefs towards algorithm bias in organisations was significantly lower than in individual-use algorithms, F (1,78) =5.761, p=.019. The mean difference based on marginal means was 1.581, and the effect size was medium, eta squared= .069. *Figure 5*. Below visualises this result in a line graph.

Figure 5. Line Graph Displaying the Difference Between the Estimated Marginal Mean Efficacy Beliefs towards Algorithm Bias for the Video and No Video Condition Within Organisational Algorithms (1) and Individual use (2)



H_3: There will be a significant interaction between the educational video and algorithm type.

There was no significant interaction between algorithm type and the educational video, thus H_3 was rejected, F (1,78) =0.041, p=.840. The observed power was .055. As seen in *Figure 5*. There is clearly no interaction between the independent variables. The full ANOVA output tables can be found in Appendix M.

4. Discussion (1643 words)

This study explored a gap in the literature by investigating the impact of an educational video on participants' efficacy beliefs towards algorithmic bias. It employs a unique multi-disciplinary lens by adapting the HAII TIME theory by Sundar (2020) from media psychology, and Bandura's (1986) Social Cognitive theory from health psychology, which both highlight the relevance of prior experience for triggering cognitive heuristics and shaping efficacy beliefs. Using a quasi-experimental design, this study demonstrated a causal relationship between the presence of an educational video and algorithm type (organisational and individual use) on the participants' efficacy beliefs towards algorithmic bias. The theoretical frameworks demonstrate that traditional psychological theories such as Bandura's (1986) Social Cognitive theory, can intersect with modern theories of Human AI interaction i.e. Sundar's (2020) HAII TIME theory, to examine behaviour in technological contexts. Whilst previous psychological studies into algorithmic bias have lacked a nuanced perspective, the combination of these theories could provide new insights. Furthermore, the inclusion of an educational video brings an unexplored factor to the existing literature.

4.1 Educational Video

Contrastingly to the studies conducted by Hilsman and Dodson (2025) and Lee et al. (2024) the efficacy beliefs towards algorithmic bias in both organisational and individual algorithms was significantly lower for the participants who had watched the educational video. This may be because the information in the video was largely conceptual, rather than skills based (Brannon et al., 2022). For example, the video used by Lee et al., (2024) was 15 minutes long, and outlined specific pain management strategies. Perhaps the 5~minute video used in this study examined the social implications of algorithmic bias but did not explicitly describe solutions that participants could implement in their daily lives. Bandura (1986) theorises that discriminatory systems distance outcome expectations from efficacy judgements, as discrimination means equal performance does not lead to equal outcomes. Perhaps the social bias presented in the video, reduced participants' confidence to perform, given

their efforts might be redundant. Although Bandura (1986) suggests that efficacy belief judgements are separate from outcome expectations in discriminatory situations, these results indicate otherwise.

Das and London (2017) suggest that the word bias has a negative connotation, thus algorithmic bias is generally regarded negatively within the literature. Perhaps the video triggered cognitive heuristics surrounding bias, which led to the participants holding a negative view of algorithmic bias, leading to lower efficacy beliefs. These results provide evidence that the aspect of prior experience, as highlighted in Sundar's (2020) HAII TIME model, is relevant in shaping or triggering cognitive heuristics. However, a deeper understanding of the concept of algorithmic bias does not necessarily increase the participant's efficacy beliefs. Bandura (1986) proposes that an efficacious technique requires an understanding of the organization and execution required to complete a task, perhaps this information does not come across in the video. The educational video provides details of biased outcomes but not the means to provide a desired outcome, which overall negatively impacts the participant's efficacy beliefs.

4.2 Algorithmic bias in organisational and individual use algorithms

The results of this study display that there are significant differences between efficacy beliefs towards algorithmic bias between organisational and individual use algorithms. The findings of Overbye-Thompson et al (2025), were replicated, given the participants had lower efficacy beliefs towards organisational algorithms. Despite the information provided in the educational video, participants still had lower efficacy beliefs towards algorithmic bias in organisational algorithms. This could be because organisational algorithms do not offer the key aspects of the action path in Sundar's (2020) HAII TIME theory. In the example of a hiring algorithm, the aspects of interaction, agency, social exchange, and mutual augmentation are missing, which likely negatively impacts the user's efficacy beliefs given there are limited actions they can take (Sundar, 2020).

Ghasemaghaei (2026) explored how inconsistency between an organisation's values and the transparency or outcomes from their AI, negatively impacts user's trust. While an organisation might explicitly endorse diversity, their hiring algorithm could implicitly discriminate against candidates (Starke, 2020). The lowest efficacy beliefs of participants were for those who watched the video towards algorithmic bias in organisational algorithms. Possibly, this is because of the discrepancies between what organisations aim to achieve with their algorithms, and the biased outcomes which were presented in the video.

4.3 Strengths and Limitations

This study contributes to a gap in the psychological literature by adding the element of an educational video to an exploration of efficacy beliefs towards algorithmic bias in organisational and individual use algorithms. A quasi-experimental design facilitates a controlled environment that has allowed for causal relationship to be drawn between the variables in this study. The design of this study was also time and cost-effective due to the publicly available educational video (Brannon, 2022). This gives the design of the study replicability, which is something other studies in the area have lacked (Gutiérrez-Santuiste et al., 2025). The pilot study informed changes in survey design to ensure that the formatting was as accessible as possible. The questionnaire is based on the GSE by Schwarzer and Jerusalem (1995), which has shown high construct and cross-cultural validity. Lastly, the combination of the theoretical frameworks by Bandura (1986) and Sundar (2020) adds nuance and depth to the findings, which previous psychological research into algorithmic bias has lacked.

This study lacks ecological validity, which is a fault of a quasi-experimental design. Though the factor of prior experience was manipulated via the educational video, perhaps their AI literacy could have been measured as an extraneous variable. Especially given the statistical effect became insignificant when controlling for prior experience with AI in the study by Petzel and Sowerby (2025). Furthermore, the demographic characteristics as explored in the study by Overbye-Thompson et al. (2025) were not explored. These might have had an

extraneous effect on the results, considering Overbye-Thompson et al. (2025) and Gutiérrez-Santuiste et al., (2025) found significant differences between genders. Another demographic aspect which has not been explored is age. The convenience sampling of this study meant that the findings might not be generalisable to the broader population, especially since most participants were college students under the age of 22.

4.4 Theoretical and Practical implications

This study has strong theoretical foundations as it expands on the HAII TIME theory by Sundar (2020) by displaying the significant effect of prior experience, which is also a factor highlighted by Bandura (1986). As the world becomes increasingly digitalised, psychological inquiry needs to be made for behaviours in technological contexts. Prior experience, in the form of the educational video negatively impacted participants' efficacy beliefs. As Bandura (1986) theorises, an understanding of the organisation and execution of Task is required for an efficacious technique, the video did not sufficiently outline the organisation or execution of strategies towards algorithmic bias. The biased outcomes of algorithmic bias were explored, which suggested that equal performances would not present equal outcomes. It appears that this negatively impacted participants efficacy beliefs, which slightly contradicts which Bandura's theory that discriminatory systems separate outcome expectations from efficacy judgements. In this instance, the negative outcome expectations negatively impacted the participants' efficacy beliefs.

As Sundar's (2020) action path suggests, interaction, agency, social exchange, and mutual augmentation are necessary within an algorithm to form the UX and trust of an AI medium. Considering organisational algorithms lack these aspects, the results display that the efficacy beliefs of participants are negatively impacted when these aspects are missing. As Ghasemaghaei (2026) suggests trust is also negatively impacted when the moral values of the organisation contradict with the outcomes of the algorithm.

The results of this study could inform the development of an educational video which aims to increase efficacy beliefs towards algorithm bias, specifically by explicitly describing the organisation and execution of tasks required to cope with this bias, as highlighted by

Bandura (1986). Organisational algorithms must have the aspects which are highlighted within the action path of the HAII TIME by Sundar's (2020) for users to have efficacy towards them. Trust will also be cemented once organisations ensure that their values, such as diversity, are reflected in the outcomes of their algorithms (Ghasemaghaei, 2026).

4.5 Future research

In future, a range of educational videos could be explored to evaluate different techniques for promoting efficacy beliefs towards algorithmic bias in organisational and individual use algorithms. The demographic factors of age, gender, and ethnicity could also be explored in an Irish context, to explore whether the findings of Overbye-Thompson et al., (2025) are generalisable. Perhaps, the efficacy beliefs could be compared across demographic groups, to see if an educational video can reduce discrepancies. The factor of AI literacy, which might have an extraneous effect on the results could also be controlled for, to test whether the educational video has an impact on efficacy beliefs when existing AI literacy is factored out. Adding qualitative elements could also add depth to the findings and further inform the development of an educational video that promotes efficacy towards algorithmic bias. A broader sample must be collected from, to determine if the findings are generalisable to the population. Another avenue which has not yet been explored is the impact of trust and attitudes towards AI, on efficacy beliefs towards algorithm bias.

4.6 Conclusion

In conclusion, this study displayed how an educational video made the participants aware of biased outcomes due to algorithmic bias, which significantly lowered their efficacy beliefs towards both domains of algorithmic bias. The efficacy beliefs of participants were significantly lower towards algorithmic bias in organisational algorithms, which could have been due to the lack of aspects in the action path of Sundar's (2020) HAII TIME theory. Both the educational video, and algorithm type (organisational and individual use) had an independent effect on efficacy beliefs. The findings of this study expand on Bandura's (1986) theory of efficacy beliefs, that emphasise contextual understanding of a task as a foundation of efficacious techniques. The findings imply increased understanding can sometimes decrease efficacy beliefs, specifically regarding a discriminatory system. The workarounds for algorithmic bias that are presented within academia must be communicated to users in an accessible format, potentially, an educational video (Overbye-Thompson & Rice, 2025)

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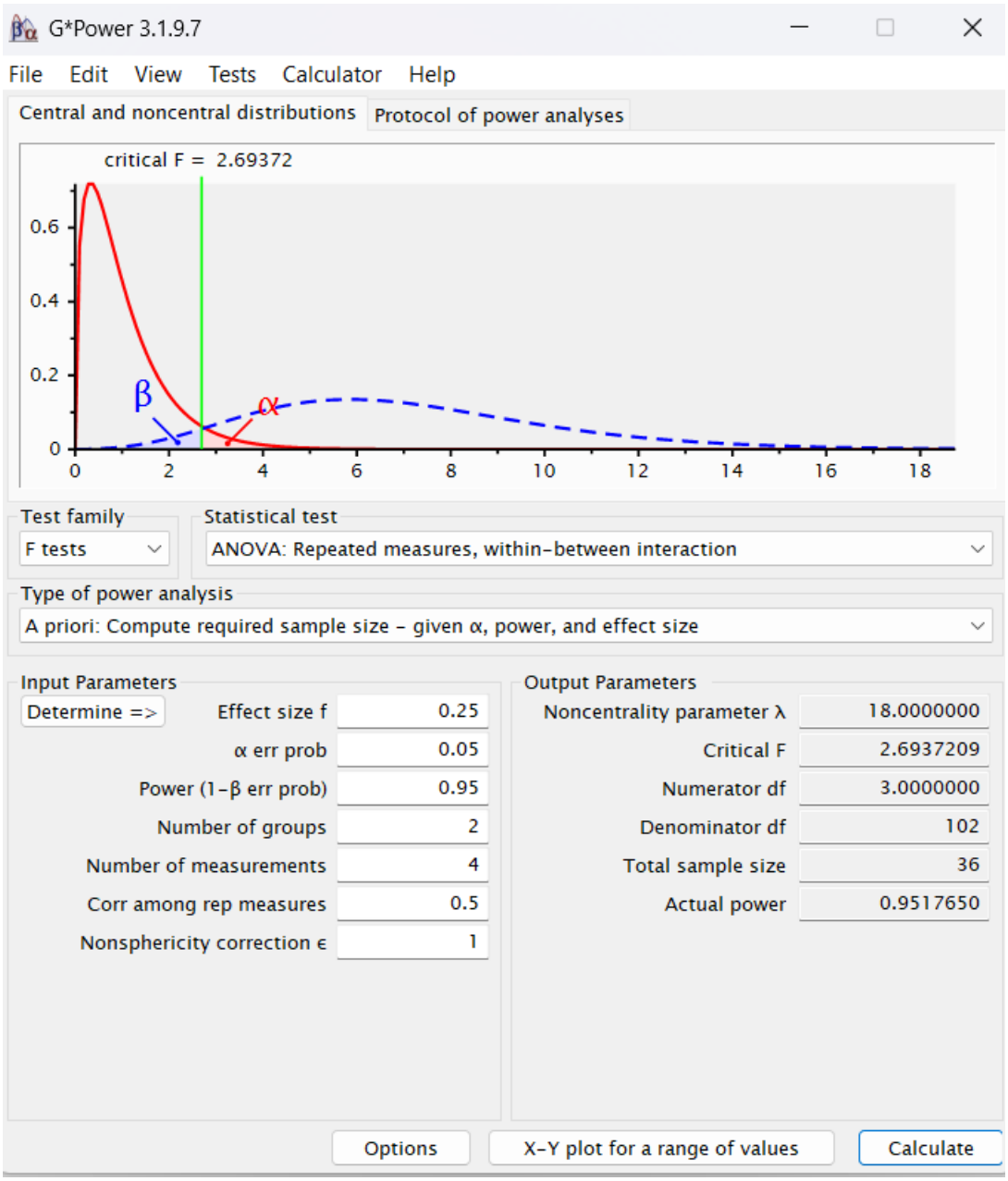
6. Appendices

A. G*Power Analysis



B. Efficacy beliefs: Organisational algorithms questionnaire

Efficacy beliefs for Organizational Algorithms (O2)

For this set of items, please think about bias in algorithms that are used by organizations. Examples of Organizations could be companies, governments, or non governmental organizations. An Algorithm is a machine or computer that performs a set of tasks.

Examples of Algorithms that are used by Organizations include facial recognition used in public spaces like airports or hiring algorithms that are used to determine if someone received an interview for a job.

Please tell us how true the following statements are to you:

1 = Not True at All
2 = Slightly True
3 = Moderately True
4 = Very True
5 = Exactly True

10

I could always manage to solve difficult problems relating to algorithm bias in algorithms that are used by organizations if I try hard enough

1 2 3 4 5

11

If confronted with algorithm bias in algorithms that are used by organizations, I can find the means to get what I want

1 2 3 4 5

12

It is easy for me to stick to my aims and accomplish my goals if confronted with algorithm bias in algorithms that are used by the organizations

1 2 3 4 5

13

I am confident that I could deal efficiently with unexpected events related to algorithm bias in algorithms that are used by organizations

1 2 3 4 5

14

Thanks to my resourcefulness, I know how to handle unforeseen situations relating to algorithm bias in algorithms that are used by organizations

1	2	3	4	5

15

I can solve most problems relating to algorithm bias in algorithms that are used by organizations if I invest the necessary effort

1	2	3	4	5

16

I can remain calm when facing algorithm bias in algorithms that are used by organizations because I can rely on my coping abilities

1	2	3	4	5

17

When I am confronted with algorithm bias in algorithms that are used by organizations, I can usually find several solutions

1	2	3	4	5

18

If I am in trouble relating to algorithm bias in algorithms that are used by organizations I can usually think of a solution

1	2	3	4	5

19

I can usually handle algorithm bias in algorithms that are used by organizations

1	2	3	4	5

C. Efficacy beliefs: Individual use algorithms questionnaire

Efficacy Beliefs for Individual Use Algorithms (I2)

For this set of items, please think about algorithms that are used by individuals (i.e. yourself, or other people on an individual basis). An Algorithm is a machine or computer that performs a set of tasks.

Examples include facial recognition used on your phone (e.g., social media facial filters, facial recognition for phone unlock), automatic water faucets that use an image sensing algorithm to function.

Please tell us how true the following statements are to you:

1 = Not True at All
2 = Slightly True
3 = Moderately True
4 = Very True
5 = Exactly True

20

I could always manage to solve difficult problems relating to algorithm bias in algorithms that are used by individuals if I try hard enough

1	2	3	4	5

21

If confronted with algorithm bias in algorithms that are used by individuals, I can find the means to get what I want

1	2	3	4	5

22

It is easy for me to stick to my aims and accomplish my goals if confronted with algorithm bias in algorithms that are used by individuals

1	2	3	4	5

23

I am confident that I could deal efficiently with unexpected events related to algorithm bias in algorithms that are used by individuals

1	2	3	4	5

24

Thanks to my resourcefulness, I know how to handle unforeseen situations relating to algorithm bias in algorithms that are used by individuals

1	2	3	4	5

25

I can solve most problems relating to algorithm bias in algorithms that are used by individuals if I invest the necessary effort

1	2	3	4	5

26

I can remain calm when facing algorithm bias in algorithms that are used by individuals because I can rely on my coping abilities

1	2	3	4	5

27

When I am confronted with algorithm bias in algorithms that are used by individuals, I can usually find several solutions

1	2	3	4	5

28

If I am in trouble relating to algorithm bias in algorithms that are used by individuals I can usually think of a solution

1	2	3	4	5

29

I can usually handle algorithm bias in algorithms that are used by individuals

1	2	3	4	5

D. Link to the Educational Video

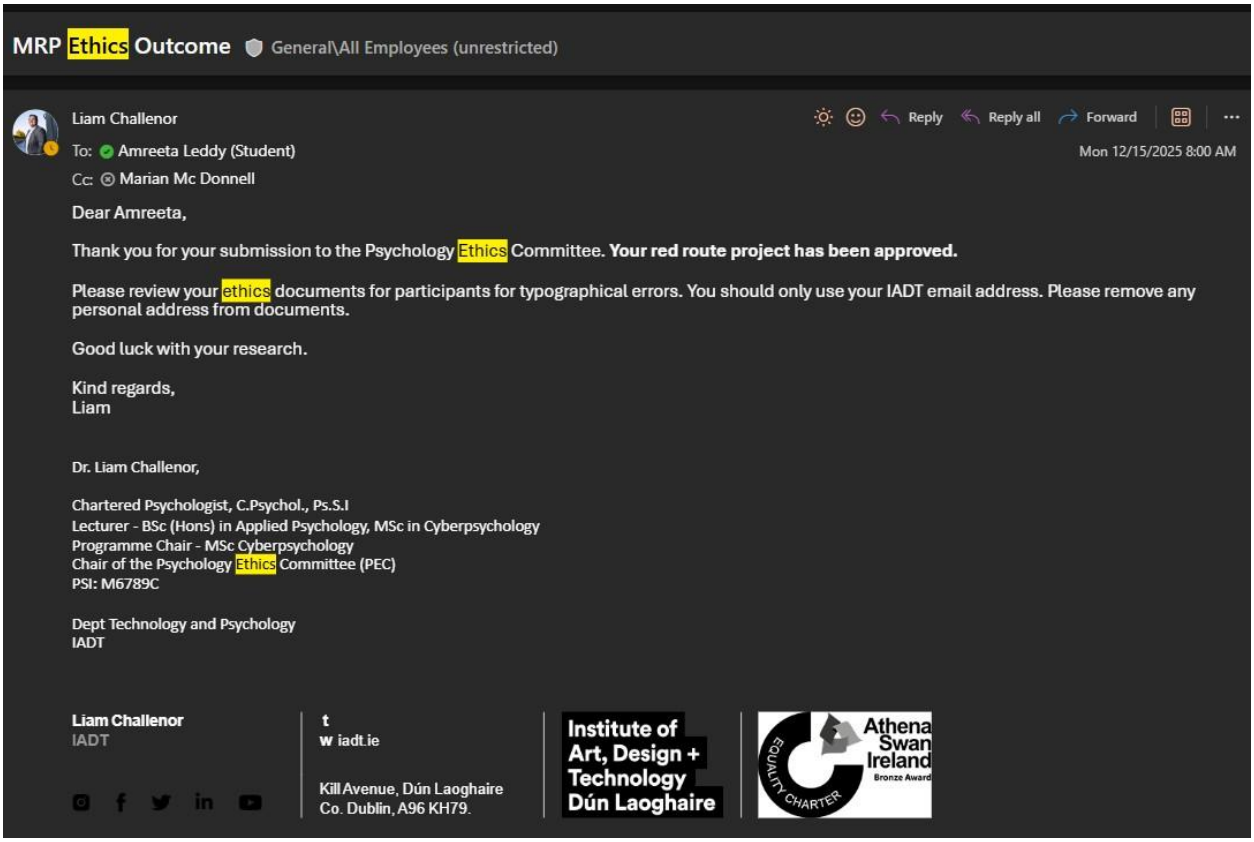
AI & Bias - So What's the Solution?

Below is a link for an educational video, please click on the link and watch the full video

Once you have watched the video in a different tab, return to this screen and click next. (O2)

https://www.youtube.com/watch?v=xvb_A_qzXo4

E. Ethics approval



MRP Ethics Outcome General\All Employees (unrestricted)

Liam Challenor

Reply Reply all Forward

To: Amreeta Leddy (Student)

Mon 12/15/2025 8:00 AM

Cc: Marian Mc Donnell

Dear Amreeta,

Thank you for your submission to the Psychology Ethics Committee. **Your red route project has been approved.**

Please review your ethics documents for participants for typographical errors. You should only use your IADT email address. Please remove any personal address from documents.

Good luck with your research.

Kind regards,
Liam

Dr. Liam Challenor,

Chartered Psychologist, C.Psychol., Ps.S.I
Lecturer - BSc (Hons) in Applied Psychology, MSc in Cyberpsychology
Programme Chair - MSc Cyberpsychology
Chair of the Psychology Ethics Committee (PEC)
PSI: M6789C

Dept Technology and Psychology
IADT

Liam Challenor
IADT

t
w iadt.ie

Kill Avenue, Dún Laoghaire
Co. Dublin, A96 KH79.

Institute of Art, Design + Technology Dún Laoghaire

Athena Swan Ireland Bronze Award

F. Information sheet

Information Sheet

Title of project: Exploring the Impact of an Educational Video and Algorithm Type on Efficacy Beliefs towards Algorithmic Bias.

You are being invited to take part in the research Exploring the Impact of an Educational Video and Algorithm Type on Efficacy Beliefs towards Algorithmic Bias. This project is being undertaken by Amreeta Leddy for our major research project as part of the BSc (Hons) in Applied Psychology, IADT. Before you decide whether you wish to take part, it is important for you to understand why this research is being done and what it will involve.

Please take time to read this information carefully and discuss it with someone you trust. If there is anything that is unclear or if you would like more information please ask, our contact details are at the end of this information sheet.

Thank you for reading this.

What is the purpose of the project?

Algorithmic Bias is a functional aspect of Artificial Intelligence Technology that results in unequal outcomes for users. There may be useful kinds of Algorithmic Bias, such as filtering social media feeds when Users show preferences for one kind of content versus another, or potentially harmful kinds of Algorithmic Bias such as Hiring algorithms showing preferences for people who are overrepresented in a company. This bias can come from the person programming the algorithm, datasets, or even the User themselves. Either way, Algorithms do not have the capacity to critically think, while people can. This study aims to explore the knowledge undergraduate students have in relation to this topic. Please be as honest as you can.

What is involved?

If you choose to participate you will be asked demographic questions about your age and gender. You will then be filtered into one of two groups. The first group will be watching an educational video. The second group will be directed to a questionnaire. All participants will be directed to answer questions on their beliefs surrounding Algorithmic Bias. The first questionnaire will ask you about your beliefs towards Organizational Algorithms e.g. facial recognition algorithm at the airport. The second questionnaire will ask you about your beliefs towards Individual-use Algorithms, e.g. google search algorithm. This study will take approximately 10 number of minutes.

When you submit this form, it will not automatically collect your details like name and email address unless you provide it yourself.

Information sheet

Do I have to take part? You are free to decide whether you wish to take part or not. If you do decide to take part, you will be asked to sign a consent form that lets us know you have read this information sheet and understand what is involved in the research. You are free to withdraw from this study at any time and without giving reasons. Choosing to either take part or not take part in the study will have no impact on your marks, assessments or future studies.

What are the disadvantages and risks (if any) of taking part?

The following questionnaire will ask you questions about your confidence about dealing with Algorithms that are used by both Organizations, and Individuals. Risks may include distress from recollecting unpleasant memories and feelings about negative experiences you might have had with this kind of bias.

What are the possible benefits of taking part?

We cannot promise the study will help you, but the information we get from the study will help to increase the understanding of how people can increase confidence towards Algorithmic (AI) Bias outcomes.

How will my information be used?

Your responses to the questionnaire will be combined with all other participants data and statistically analysed. No individual's data will be identifiable in the final report. The results of this analysis will be reported in the thesis for the BSc (Hons) in Applied Psychology in the Dun Laoghaire Institute of Art, Design & Technology. This can be requested through the library at IADT, or by emailing the researcher or supervisor at n00223065@iadt.ie or marian.mcdonnell@iadt.ie . This study may also be published in an academic journal article and may be written about for blog posts or media articles, and these can be requested from the researcher.

Information sheet

How will my data be protected? Under the EU General Data Protection Regulation (GDPR) the legal basis for collecting data for scholarly research is that of public interest. The regulations regarding the protection of your data will be followed. Only data which is needed for analysis will be collected. By giving your consent to take part in the study you are consenting to the use of your data as detailed in this information sheet. The data will be retained by the researcher for at least one year and may be retained for up to 7 years if the results of the study are published in certain capacities (e.g. in a journal article). There is also a possibility that the fully anonymised dataset may be submitted to a journal and made available to other researchers and academics worldwide for verification purposes, but if this occurs it will be ensured that you are not identifiable from the data. As the supervisor on this project, I, Marian McDonnell am responsible for ensuring that all datasets will be stored in accordance with GDPR regulations and those which are not submitted to a journal will be fully deleted on or before 23/02/2033. Only the researcher and supervisor for this project will have access to the data collected in this study. This data will be stored in a password protected cloud account. None of the data will be identifiable due to the anonymised participant codes. All data will be kept by the researcher for a maximum of 1 year, and the supervisor for up to 7 years. After this it will be permanently deleted. You will find contact information for IADT's Data Protection Officer, David Smith, and more information on your rights concerning your data at https://iadt.ie/about/your-rights-entitlements/gdpr/

Who has reviewed the study?

This study has been approved by the IADT Psychology Ethics Committee.

Information sheet

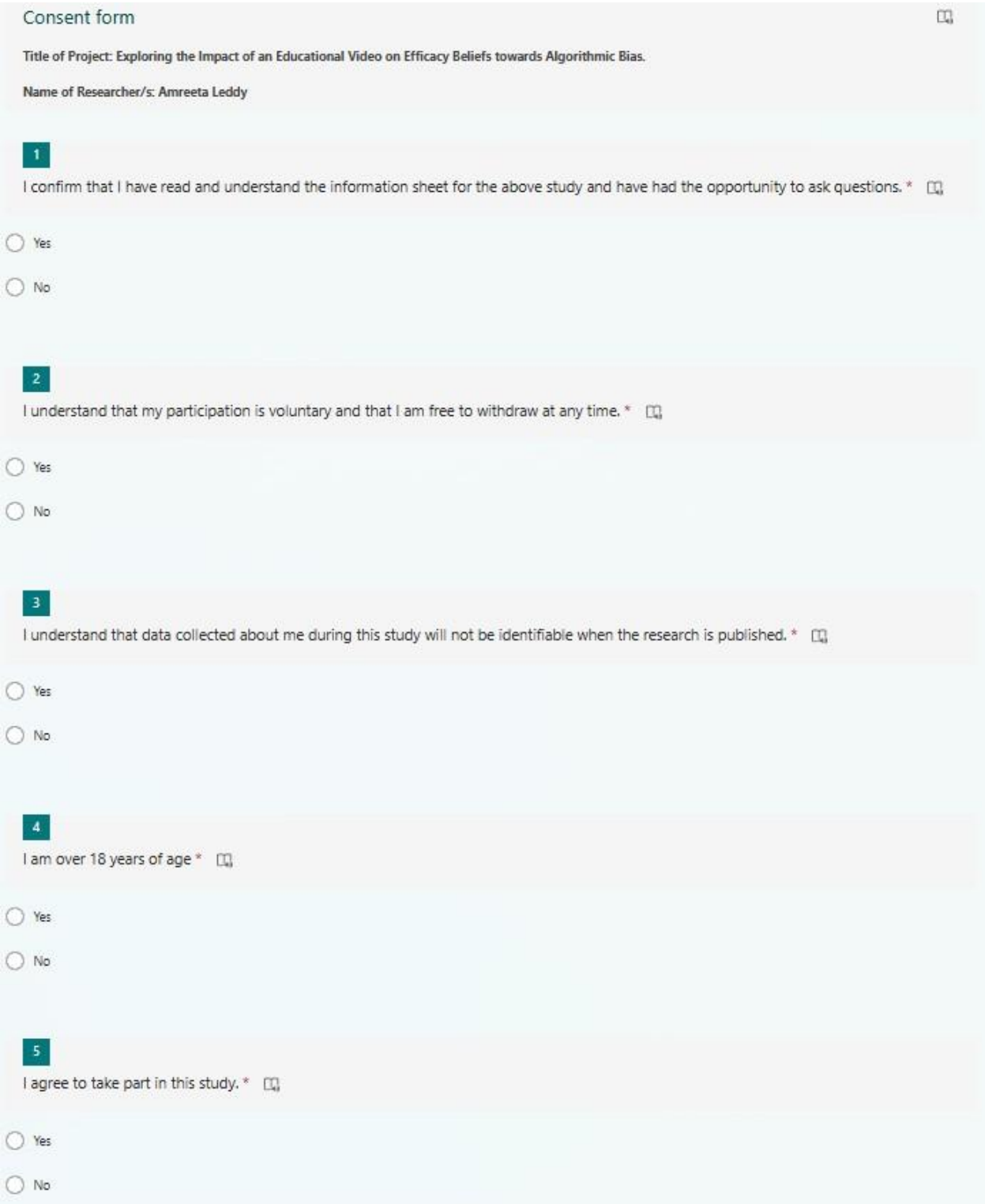
What if you have any questions or there is a problem?

If you have a concern about any aspect of this study, you may wish to speak to the researcher(s) who will do their best to answer your questions. You should contact Amreeta Leddy (n00223065@iadt.ie) or their supervisor Marian McDonnell, (marian.mcdonnell@iadt.ie)

Thank you again for taking the time to participate in this research.

If you have any questions about this study, please contact the researcher or supervisor at n00223065@iadt.ie or marian.mcdonnell@iadt.ie

G. Consent form



Consent form

Title of Project: Exploring the Impact of an Educational Video on Efficacy Beliefs towards Algorithmic Bias.

Name of Researcher/s: Amreeta Leddy

1

I confirm that I have read and understand the information sheet for the above study and have had the opportunity to ask questions. *

- Yes
- No

2

I understand that my participation is voluntary and that I am free to withdraw at any time. *

- Yes
- No

3

I understand that data collected about me during this study will not be identifiable when the research is published. *

- Yes
- No

4

I am over 18 years of age *

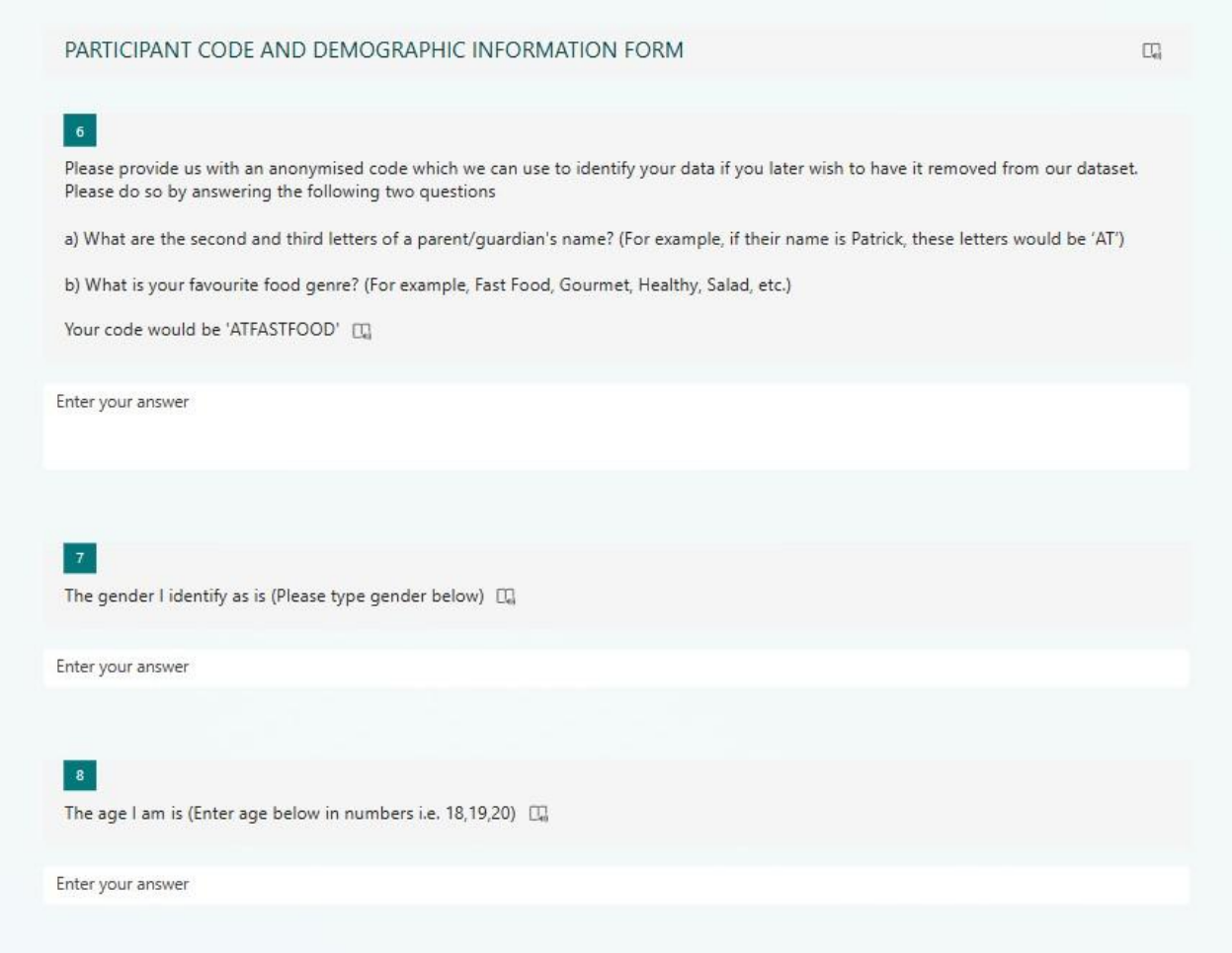
- Yes
- No

5

I agree to take part in this study. *

- Yes
- No

H. Participant code and Demographic questions



PARTICIPANT CODE AND DEMOGRAPHIC INFORMATION FORM

6

Please provide us with an anonymised code which we can use to identify your data if you later wish to have it removed from our dataset. Please do so by answering the following two questions

a) What are the second and third letters of a parent/guardian's name? (For example, if their name is Patrick, these letters would be 'AT')

b) What is your favourite food genre? (For example, Fast Food, Gourmet, Healthy, Salad, etc.)

Your code would be 'ATFASTFOOD'

Enter your answer

7

The gender I identify as is (Please type gender below)

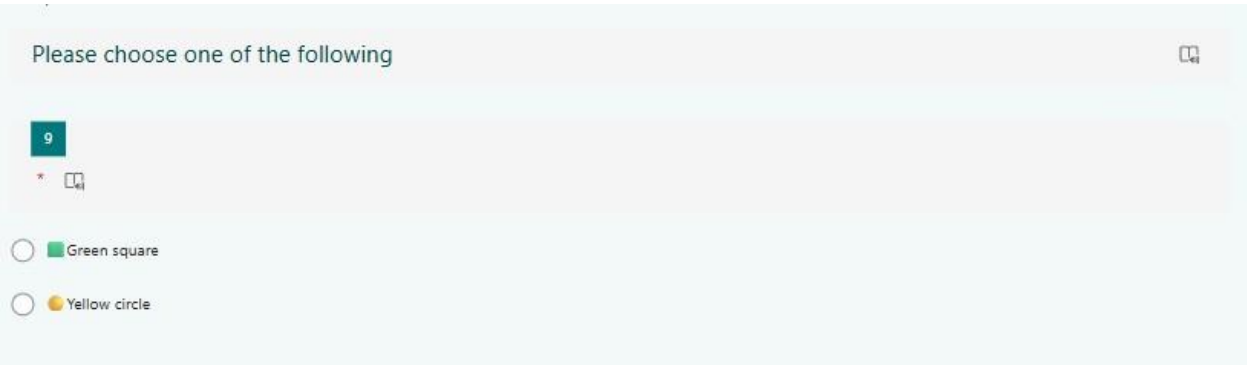
Enter your answer

8

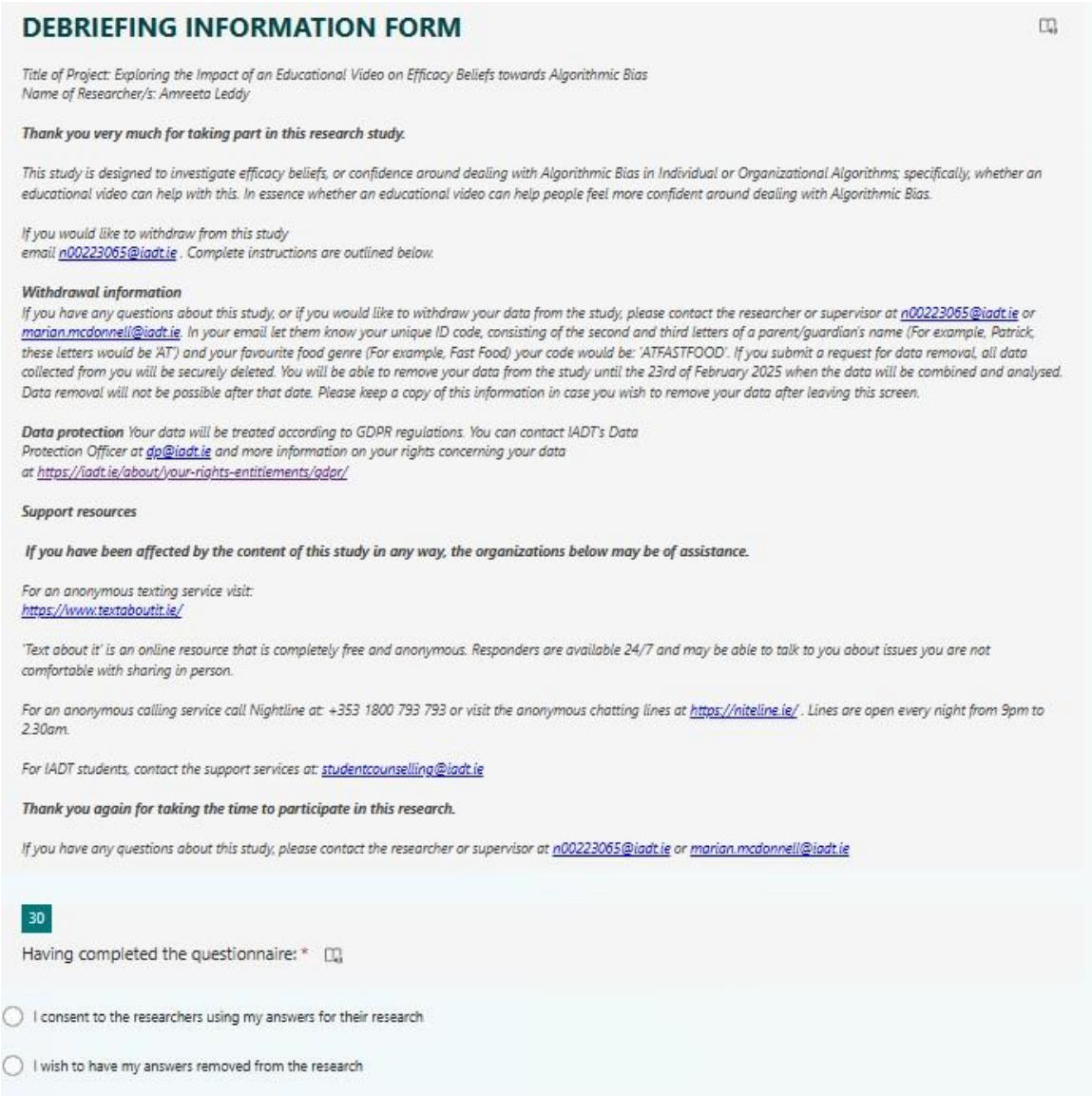
The age I am is (Enter age below in numbers i.e. 18,19,20)

Enter your answer

I. Branching question



J. Debriefing form



K. SPSS output of descriptives

Descriptives

			Statistic	Std. Error
Efficacy Beliefs: Organisational Algorithms	Mean		30.61	1.046
	95% Confidence Interval for Mean	Lower Bound	28.53	
		Upper Bound	32.69	
	5% Trimmed Mean		30.61	
	Median		31.00	
	Variance		87.481	
	Std. Deviation		9.353	
	Minimum		10	
	Maximum		50	
	Range		40	
	Interquartile Range		11	
	Skewness		-.017	.269
	Kurtosis		-.106	.532
Efficacy Beliefs: Individual use Algorithms	Mean		32.20	.964
	95% Confidence Interval for Mean	Lower Bound	30.28	
		Upper Bound	34.12	
	5% Trimmed Mean		32.14	
	Median		32.00	
	Variance		74.289	
	Std. Deviation		8.619	
	Minimum		14	
	Maximum		50	
	Range		36	
	Interquartile Range		12	
	Skewness		.092	.269
	Kurtosis		-.310	.532

L. SPSS output assumptions

Mauchly's Test of Sphericity[a]

Measure: MEASURE_1

Within Subjects Effect	Mauchly's W	Approx. Chi-Square	df	Sig.	Epsilon[b] Greenhouse-Geisser	Epsilon[b] Huynh-Feldt	Epsilon[b] Lower-bound
Algorithmtype	1.000	.000	0	.	1.000	1.000	1.000

Tests the null hypothesis that the error covariance matrix of the orthonormalized transformed dependent variables is

Levene's Test of Equality of Error Variances[a]

		Levene Statistic	df1	df2	Sig.
TotalOrg	Based on Mean	.389	1	78	.535
	Based on Median	.311	1	78	.578
	Based on Median and with adjusted df	.311	1	76.551	.578
	Based on trimmed mean	.367	1	78	.546
Total Ind	Based on Mean	.172	1	78	.679
	Based on Median	.185	1	78	.668
	Based on Median and with adjusted df	.185	1	77.872	.668
	Based on trimmed mean	.168	1	78	.683

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.

Box's Test of Equality of Covariance Matrices [a]

Box's M	1.698
F	.550
df1	3
df2	1637091.988
Sig.	.648

M. SPSS output ANOVA tables

Tests of Within-Subjects Effects

Measure: MEASURE_1

Source		Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[a]
Algorithmtype	Sphericity Assumed	99.711	1	99.711	5.761	.019	.069	5.761	.659
	Greenhouse-Geisser	99.711	1.000	99.711	5.761	.019	.069	5.761	.659
	Huynh-Feldt	99.711	1.000	99.711	5.761	.019	.069	5.761	.659
	Lower-bound	99.711	1.000	99.711	5.761	.019	.069	5.761	.659
Algorithmtype * Condition	Sphericity Assumed	.711	1	.711	.041	.840	.001	.041	.055
	Greenhouse-Geisser	.711	1.000	.711	.041	.840	.001	.041	.055
	Huynh-Feldt	.711	1.000	.711	.041	.840	.001	.041	.055
	Lower-bound	.711	1.000	.711	.041	.840	.001	.041	.055
Error(Algorithmtype)	Sphericity Assumed	1349.983	78	17.307					
	Greenhouse-Geisser	1349.983	78.000	17.307					
	Huynh-Feldt	1349.983	78.000	17.307					
	Lower-bound	1349.983	78.000	17.307					

[a] Computed using alpha = .05

Tests of Between-Subjects Effects

Measure: MEASURE_1

Transformed Variable: Average

Source	Type III Sum of Squares	df	Mean Square	F	Sig.	Partial Eta Squared	Noncent. Parameter	Observed Power[a]
Intercept	158479.671	1	158479.671	1153.045	<.001	.937	1153.045	1.000
Condition	708.421	1	708.421	5.154	.026	.062	5.154	.611
Error	10720.672	78	137.445					

[a] Computed using alpha = .05

Pairwise Comparisons

Measure: MEASURE_1

(I) Condition	(J) Condition	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
Video	No Video	-4.214*	1.856	.026	-7.909	-.519
No Video	Video	4.214*	1.856	.026	.519	7.909

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.

Pairwise Comparisons

Measure: MEASURE_1

(I) Algorithmtype	(J) Algorithmtype	Mean Difference (I-J)	Std. Error	Sig.[b]	95% Confidence Interval for Difference[b]	
					Lower Bound	Upper Bound
1	2	-1.581*	.659	.019	-2.892	-.270
2	1	1.581*	.659	.019	.270	2.892

Based on estimated marginal means

*. The mean difference is significant at the .05 level.

b. Adjustment for multiple comparisons: Bonferroni.