The "Nessa" System: Can Images from Age-Related 'Reminiscence Bumps' Help Us Separate Grown-Ups from Kids?

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Abstract

As children increasingly operate online as independent agents, online service providers have to find ways to prevent them from going into adult-only spaces. Doing this in a privacy-preserving way is non-trivial, because most service providers require proof of identity, in order to verify a users age. We suggest benefiting from a reliable 'reminiscence bump' which occurs at a predictable time in an adult's life. Much of what occurs in this bump is retained for life, and this includes a memory of famous personages. We plan to display a number of images from the person's stated-age reminiscence bump to test recognition ability. Their performance in this task should signal the adulthood of the user. Our studies found that participants had an accuracy rate of 79.61% when asked to identify famous figures from within their reminiscence bump, compared to an average rate of 54.98% when presented with famous figures from periods outside their 'reminiscence bump'. We suggest ways in which this could be used as part of a privacy preserving online age assurance solution called "Nessa".

1 Introduction

Current age verification mechanisms in the digital world do not replicate the stringent processes that exist in the physical world to prevent children from purchasing adult products, entering venues or accessing adult services. A report published in 2016 by the National Society for the Prevention of Cruelty to Children (NSPCC), Middlesex University and The Children's Commission highlighted the long-term developmental harm that being exposed to adult content online can have on children [17]. The findings prompted policy promises by the UK Government to address the issue [12] which rippled across Governments globally with many introducing laws to mandate effective online age verification controls.

Even though age verification is a politically charged subject, it has proven technically challenging to implement due to a multitude of privacy and security concerns. Although a number of commercial age verification products exist in the marketplace, there remains a gap for an effective and privacy preserving mechanism that is affordable for businesses to deploy.

This research aims to discover whether it is possible to utilise people's 'reminiscence bump': a period in life where people encode a greater number of personal memories. We want to benefit from this tendency to allow us to distinguish between adults and children online. This could prove to be a viable online age assurance alternative while also being privacy preserving.

Building upon research carried out by Jarvie and Renaud [14], this study forms the first part of wider research into "*privacy-preserving online age verification*". Using knowledge checks as one method of estimating an online users age may provide an effective model for age assurance. We now report on the goals of the study reported in this paper.

This research sought to test the viability of an age assurance mechanism built on image recognition, with the images being from the person's own reminiscence bump. As such, the study had goals:

1. To discover whether people are more likely to accurately identify famous people from their specific reminiscence bump.
2. If so, whether this correlates to a reduced accuracy score when asked to identify famous people from outwith their own reminiscence bump.

This study explored the following research questions:

RQ1: *How accurately can people identify famous figures from their reminiscence bump?*

RQ2: *How accurately can people identify famous figures from outside their reminiscence bump?*

These research questions will help to inform further research and development into a privacy-preserving online age verification solution. Section 2 reviews the related research. Section 3 outlines the research methodology design. Section 4 outlines the three studies. Section 5 discusses the findings. Section 6 presents the limitations and Section 7 concludes.

2 Related Research

2.1 Age Verification

Children pervade online spaces, sometimes venturing where only adults should go. To prevent this, online age verification mechanisms are deployed [11, 22, 10, 29]. Jarvie and Renaud [14] reviewed the literature and industry practice in this respect. They discovered a wide range of processes, ranging from doing nothing or asking the user to confirm they were over 18 by either ticking a box or inputting their age or date of birth [29, 27, 5].

Jarvie and Renaud [14] proposed that an online age verification mechanism ought to be: (1) privacy preserving, (2) effective & inclusive, and (3) affordable. Their review also found that none of the popular mechanisms in current use fulfilled all of these requirements - with most violating privacy by collecting identity data, which could lead to identity theft or blackmail in rare cases.

However, one method that *does* demonstrate promise was proposed by Renaud and Maguire in 2015 [21]: they suggested using historical image recognition as an age verification mechanism. The idea is to show images that adults ought to recognise, but that children are unlikely to be familiar with. Their performance in labelling these images is likely an indicator of their actual age.

Crucially, this mechanism mirrors the way age verification is carried out in the physical world. To purchase alcohol, for example, a person has to provide proof of age but this is not recorded anywhere - it is shown to a gate keeper to confirm adulthood. As such, it is privacy preserving, and because it uses images and not any specialised hardware, it is also affordable. The real question is whether it is effective, which this study demonstrates.

This mechanism relies on the concept of the 'reminiscence bump', which we introduce next.

2.2 Reminiscence Bump

The 'reminiscence bump' is a psychological phenomena discovered in the 1980's when researchers found people over 40 years of age have a higher number of memories from the period of their life between the ages of 10-15 and 30 [15]. The reminiscence bump has been studied in a variety of contexts, with regards to music [13], Alzheimer's [4] and even global studies of the difference culture plays on our memories [6], however, not in relation to online age assurance technologies.

During adolescence and early adulthood, there are a significant amount of "firsts" and new experiences which can become core memories in someone's life [28]. Conway *et al.* suggest the increased hormonal activity during this period of life can contribute to the solidification of these memories in the mind [6]. Adding to these concepts, Bernstein and Rubin suggest that these memories follow a perceived life-script whereby people have an idea of typical life events and the age at which they happen [4]. There are different arguments as to why the reminiscence bump exists, but Fitzgerald [9] believes it is from a crucial period which is "self-defining" in a person's life.

There has been significant research and theories applied to what the reminiscence bump is and why it exists [6],[13], [15], [9], but research on its application within the technology space is limited. To apply the concept of the reminiscence bump and age assurance to authentication models, this study could provide a novel concept for verifying the adulthood of an online user.

2.3 Assurance Factors

As stated by the National Institute of Standards and Technology (NIST), there can be three factors to multi-factor authentication, something you have, something you know and something you are [19]. Although we are not looking to authenticate a user, this principle can be used to categorise age assurance mechanisms. We may ask for something the user holds, but this could reveal their identity. We could ask for something they are, like a biometric, and try to judge this for adulthood, but this, once again, violates privacy. On the other hand, we could ask for something the user should *know* without them needing to reveal their identity.

Being able to assure a user's online identity in a privacy preserving way has been an issue for a long time, and one that now applies to age assurance online. Hada and Orita [20] proposed an anonymous bi-directional link as a method for identity assurance online without the need for a user to reveal their name. This applied predominately to social media and a users "online brand" which means its application for age assurance and particularly with children, is not suitable. Similarly, there are a number of age verification products currently available, most of which require the user to identify themselves in order to prove their age.

Several vendors accept credit cards, debit cards or mobile number to verify an online users identity to confirm they are an adult [25],[1],[2],[24]. These solutions need two data points, the users identity and details about something they own, i.e. a bank card or credit card, in order to assure their identity, and therefore their age. Another type of identity and age verification check online is to use a third party to conduct a database check, such as a credit check [7],[8],[23].

However, there are new solutions which utilise AI to estimate the age of a user based on their face, rather than asking the user to identify themselves. This requires just one authentication element, something you are [30],[24].

One issue with any complicated authentication or assurance mechanism is that it can be difficult to understand and use [3]. Relying on users to accurately remember more knowledge points or input large amounts of personal details in order to gain access to online services is not particularly user friendly or privacy preserving [18], which was an important consideration as we formulated our solution. An effective, privacy-preserving and affordable online age verification solution must be easy to use and as seamless as possible for the online customer.

3 Research Design and Methodology

This was a remote study, following the Design Science methodology as it was refined through an iterative process. One of the main aims of this methodology is to investigate artifacts in context, which is a vital part of this project to ensure that the research findings can help with age verification in the future. The Nessa system is an age assurance solution which uses multiple inputs to estimate the age of an online user. The name Nessa means "uncertain"[1] which seemed apt due to its role in bringing greater certainty as to the adulthood of a user. This study forms the first part of the Nessa system, where we test our theories, refine them and communicate the findings before moving on to develop and test other artifacts which will form the Nessa system.

Participants were asked a number of questions, including their year of birth, and then asked to identify a selection of famous people selected from a database based on their age. This meant there were two elements to the study, attributes which make the person who they are, and questions which gauge what they know, similar to authentication [19].

Our mechanism poses two challenges: (1) questions, and (2) image recognition.

[1] `https://www.behindthename.com/name/neasa`

3.1 Materials

(1) Questions:
We wanted to ask people questions, the answers to which would indicate their actual age. Someone who is over 18 can be expected to have voted and have an occupation, so these were obvious questions to ask. We also asked them for their age (to inform image choice for the second stage), and then some other questions to confirm their adulthood: their mother's age when they were born and the year and month they left school.

The questions chosen were designed to be simple for those over 18 to answer but more challenging for under 18's to work out what answer would prove adulthood.

(2) Image Recognition:
The second part builds upon the work and methodology set out by Renaud and Maguire [21]. Images of popular people from 1960-2010 were chosen in the categories of: (1) Entertainment: music, film & television, (2) World Events, (3) Iconic Figures and (4) Politicians. All are people who were in the media when and ought to be remembered by people who were living through their reminiscence bump at the time. Images were displayed in random order. The years 1960 to 2010 were chosen as this meant we could study a wide ranging group of participants aged from 18 right up to 80 plus years of age.

Google N-gram[2] was used to identify the decade that person was popular in the media. With this method, to be accepted into the study, the N-Gram would have to show a bell curve of popularity during a certain decade, but no resurgence in popularity subsequently. A resurgence was ruled out due to the fact that younger people would be more likely to recognise the person, which may impact our ability to estimate age based on image recognition. When an ideal profile was confirmed, a headshot was obtained from Wikimedia [26] to ensure that we did not violate copyright.

A list of famous figures for each decade was collated and every one was then verified using Google N-Gram. Once the famous figures had been agreed, their pictures were collated before the survey could be built. In order to appeal to a wide range of ages, it was decided that there would be 7 celebrities chosen for each decade between 1960 and 2010. The list of famous figures used across the study is shown in the Appendices.

3.2 Age Verification Process

(1) Questions:
The idea is to ask users five questions about aspects of adulthood and collect their answers. For example, instead of the user stating they are 30 years old, they will be asked to write *"thirty"*. The questions are:

1. How old are you?
2. What year and month did you leave school?
3. How old was your mum when you were born?

[2] `https://books.google.com/ngrams`

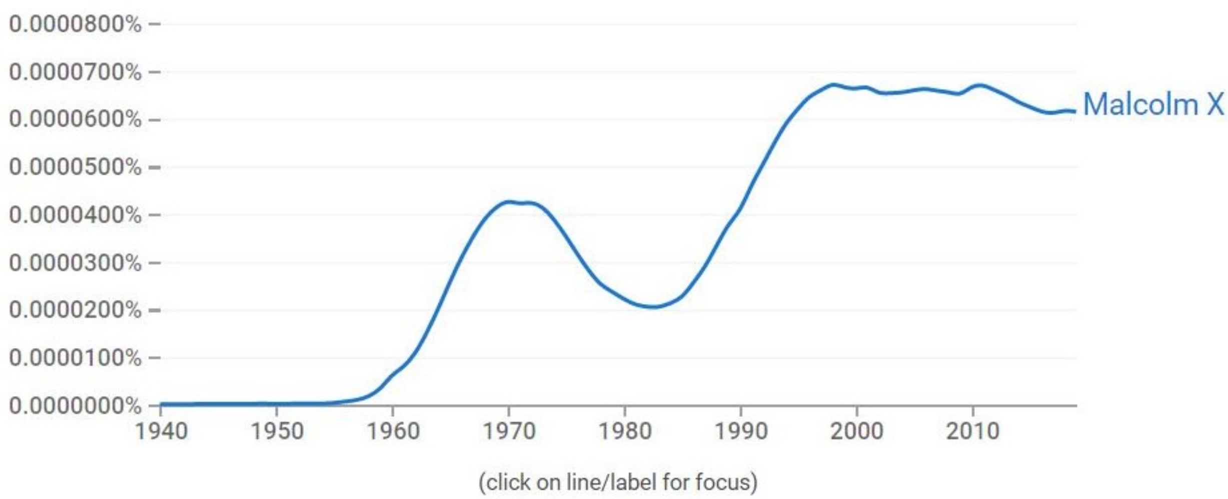

Figure 1: A poor N-gram example

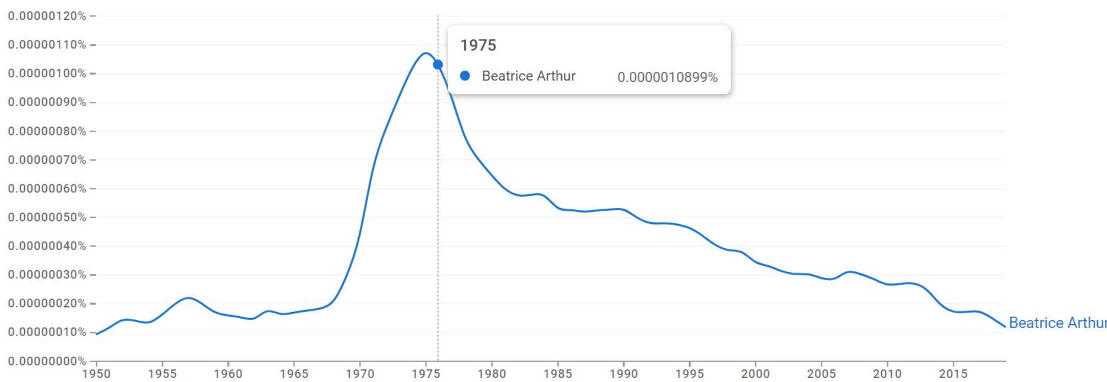

Figure 2: A good N-gram example

4. What year did you vote in your first general election?

5. What is your occupation?

These questions in particular were chosen as they may be difficult for a child to answer

(2) Image Recognition:

To begin with, based on the claimed age provided by the user, a specific decade of images was displayed one at a time. This specific decade was based on the participants calculated reminiscence bump. The decade in the middle of this bump was used to determine the images which correlate to the closest decade when they were between 15 and 25 years of age. The survey was then run again and the user was shown famous figures from outwith their reminiscence bump to determine if their accuracy score reduced. Figure 3 shows how the question was posed.

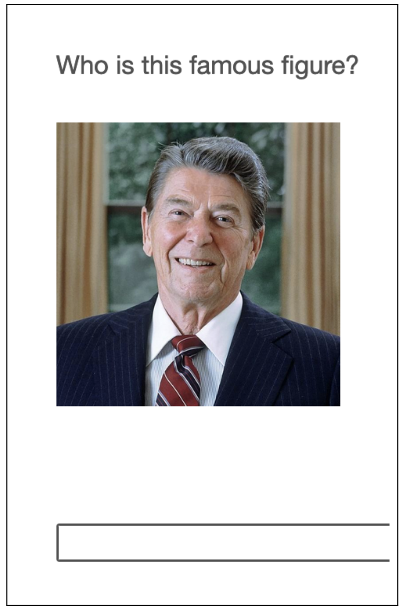

Figure 3: Recall-Based Challenge Question

3.3 Participants

Participants were recruited in January 2023 through Prolific and word of mouth with a total of 440 responses, 330 of which were paid via Prolific and all participants were UK based. Where Prolific was used, different participants were used for each study.

The participants were from a mix of backgrounds with 60% having an education level of University Bachelors degree or Graduate or professional degree. On gender balance, 54% of the participants were female, 45% were male and 1% were non-binary, third gender or preferred not to say. The vast majority of participants stated their ethnic origin as white which totalled 90% of respondent's, with 4% stating Asian, 2% Black/African/Caribbean and 4% Mixed, Other or prefer not to say.

4 Studies and Iterations

Through this iterative research, three different studies were conducted, all of which aim to answer the research questions but with slightly different methodology.

Figure 4 depicts the three different studies we carried out, all of which are described in detail in the next sections.

4.1 Study 1 - Ratification of images

The aim of the first iteration of the experiment was to understand whether the famous figures chosen for the experiment were correct.

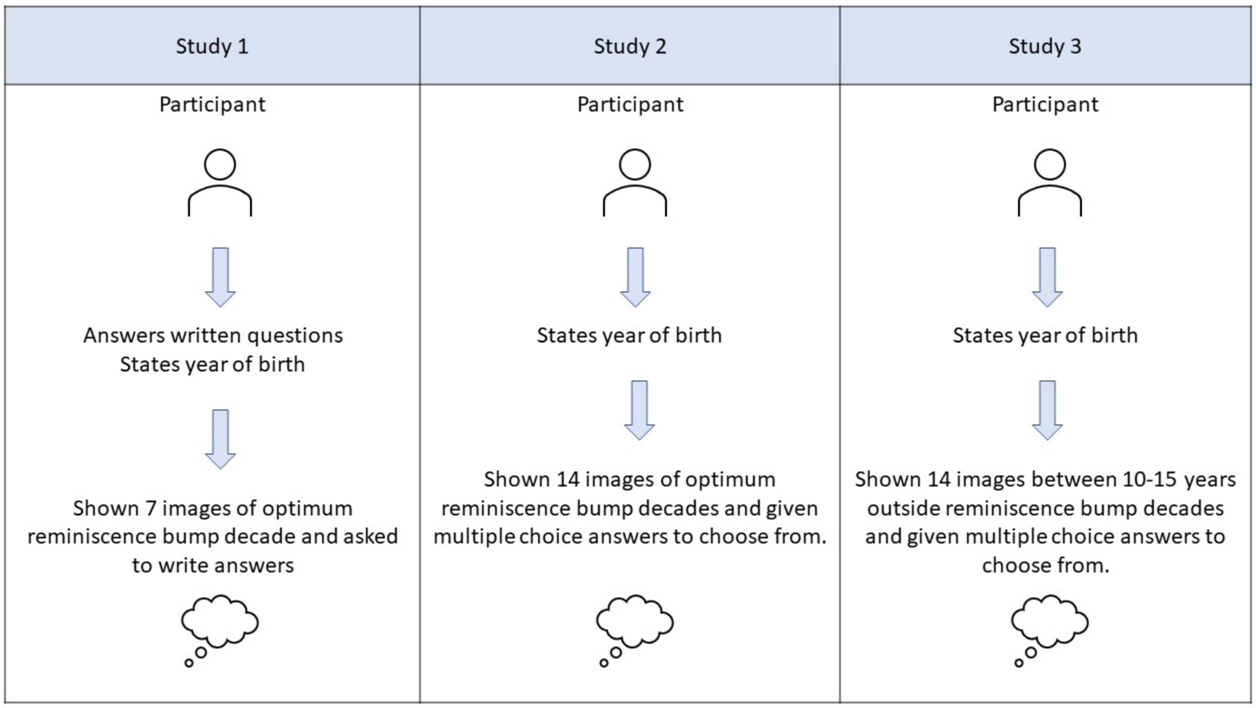

Figure 4: A summary of the three studies conducted

Using Qualtrics the participant was first asked a series of demographic questions before being asked the five knowledge questions that required written answers. A key compulsory question was for the user to state their year of birth as this decided which famous figures they were to be shown.

Based on the participants' self reported year of birth, they were shown seven images of famous figures from their matching reminiscence bump decade. The years of birth and decade presented to the participants are shown in Table 1.

Table 1: Study 1 - Reminiscence bump assignment

Decade of birth	Famous Figure Decade
<1950	1960-1969
1950-1959	1970-1979
1960-1969	1980-1989
1970-1979	1990-1999
1980-1989	2000-2009
1990-1999	2010-2019
2000-2005	2010-2019

4.1.1 Results

There were a total of 150 participants in study 1, ranging in age from 19 to 82 years of age, with 56% of participants being female, 43% male and 1% described themselves as non-binary or third gender.

Overall, the accuracy score was lower than anticipated at 58.86%. The average scores across each decade of famous figures, of which there were seven per decade, are shown in Table 2.

Table 2: Study 1 - Results

Decade Shown	Average Scores
1960's	82.85%
1970's	35.28%
1980's	71.50%
1990's	28.28%
2000's	68.57%
2010's	66.71%

Both the 1970's and 1990's had significantly lower scores and, upon further analysis, needed the most changes to profiles ahead of study 2.

4.2 Study 2 - Introduction of multiple choice

Study 2 was run in the same way as study one with a few alterations. Based on the findings of study 1, and feedback from participants, several adjustments were made to the survey and these are as follows.

4.2.1 Multiple Choice

Many of the participants commented that they recognised the face but could not remember the person's name. Others commented: "*character from* .." and successfully mentioned the movie or show the person was in but could not remember the name. For this reason, multiple choice questions were posed in study 2. For each famous Figure, 5 options were given, 4 names, and one option for "*I don't know*" with the ability to comment. Five options were used to reduce the chances of guessing success. Figure 5 shows an example of a multiple choice question.

4.2.2 Removal of written questions

Several participants objected to being asked to provide written responses. Some did not understand why they needed to answer the questions about their personal life, and others admitted they could not remember the answers to some of the questions, such as when they first voted. Others felt it was too time consuming to complete on a mobile device.

Given the focus on the famous figures, and the accessibility issues participants faced, this section was removed from subsequent studies.

4.2.3 Changes to famous figures

The results from study 1 showed that some famous figures were not well recognised. In order to refine the database, it was decided that any person with a recognition score of less than 50% would be replaced. Any person with between 50-65% would have their photo changed in case the photo itself was the problem. A total of 16 out of 42 faces were replaced and Table 7 shows the final list of famous figures used in studies 2 and 3.

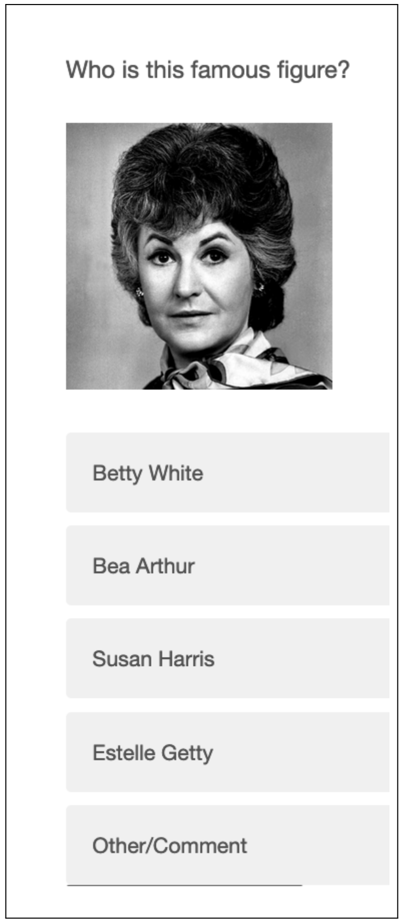

Figure 5: Recognition-Based Challenge Question

4.2.4 Reminiscence bump decades

With the removal of the written questions and some participants' reminiscence bumps spanning two decades, all participants were shown faces from two different decades.

Table 3: Study 2 - Reminiscence bump assignment

Decade of birth	Famous Figure Decade
<1950	1960's and 1970's
1950-1959	1970's and 1980's
1960-1969	1980's and 1990's
1970-1979	1990's and 2000's
1980-1989	1990's and 2000's
1990-1999	2000's and 2010's
2000-2005	2000's and 2010's

4.2.5 Results

A total of 160 participants took part, ranging in age from 19 to 88 years of age. 53% of participants were female, 45% were male and 2% described themselves as non-binary or third gender.

Compared to study 1, the accuracy score increased as anticipated to an overall accuracy score of 79.61%. This is an increase from study 1 of 18.54%, which is likely a consequence of providing the multiple choice answers (enabling recognition rather than recollection) and replacing some of the faces. The average scores across each decade of famous figures, of which there were again 7 per decade, are shown in Table 4.

Table 4: Study 2 - Results

Decade Shown	Average Scores
1960's	71.43%
1970's	68.83%
1980's	83.09%
1990's	81.70%
2000's	82.03%
2010's	77.4%

All decades showed an increase in accuracy, including the 1970's and 1990's which had the worst scores in Study 1.

4.3 Study 3 - Outside reminiscence bump

The third study reshuffled the decades participants were shown to two decades that were not in their reminiscence bump. This helped us to discover whether the accuracy scores was different in this case. All changes made in study 2 were retained for study 3. The only difference was in not matching displayed files to the person's reminiscence bump. The new decades shown based on year of birth are shown in Table 5.

4.3.1 Results

A total of 121 participants took part, ranging in age from 21 to 88 years of age. 51% of participants were female and 49% were male.

The overall accuracy score was 54.98%, which, when compared to study 2, is a decrease of 24.63%. Interestingly, the accuracy score falls significantly for those born between 1980 and 2004, with the average score being 29.59% i.e., not much more than chance given their are four name options for each face. The average scores for each decade the participants were born are shown in Table 6.

Table 5: Study 3 - Non-Reminiscence bump assignment

Decade of birth	Famous Figure Decade
<1950	1990's and 2000's
1950-1959	2000's and 2010's
1960-1969	1960's and 2010's
1970-1979	1960's and 2010's
1980-1989	1960's and 1970's
1990-1999	1970's and 1980's
2000-2005	1970's and 1980's

Table 6: Study 3 - Results

Decade born	Average Scores
<1950	67.46%
1950-1959	70.95%
1960-1969	67.35%
1970-1979	64.94%
1980-1989	27.43%
1990-2004	31.75%

4.3.2 Participant Feedback

Participants fed back that they felt the addition of multiple choice made the survey much easier to complete. Several also commented that it was enjoyable to fill in because it felt like a quiz and they wanted to give the right answers.

5 Discussion

Across the three studies, there were a total of 431 responses which gave a reasonable sample size for this research. The feedback and results from each experiment allowed changes to be made, which optimised the study and helped to obtain conclusive results.

The surveys gave quantitative data which was analysed to understand how well each decade of famous figures were recognised by the participants. Part of this study was to discover whether the famous people's faces were indeed recognisable and familiar to those whose reminiscence bump fell into the peak of the person's career. Once this was established, analysing the accuracy scores for each decade to determine whether each age group was more likely than not to determine the correct identity of the famous figures.

Table 7: Overall Average Scores

Study	Average Scores
Study 1	58.86%
Study 2	79.61%
Study 3	54.98%

The results from Study 1 were somewhat unexpected, with the accuracy rate being lower than anticipated. In particular, the 1970's and 1990's had the worst results with a combined accuracy score of just 32%. However, based on feedback from participants and the changes made for study 2, the results significantly improved.

An increase in accuracy score of almost 21% was observed in study 2 compared to study 1, bringing the average accuracy score up to almost 80%. The combination of new profiles but likely more influential, the addition of multiple choice helped the participants to perform better in the survey. For those participants in study 1 who stated they *"know the face but can't remember the name"* (tip of the tongue syndrome), the multiple choice made it easier for them to identify the correct answer.

As study 3 was to investigate the impact of asking users to identify famous figures outside their reminiscence bump, it was expected that the accuracy score would decrease. The overall result of almost 55% was still higher than anticipated but when we analyse the results by age group then the results become interesting.

For people born after 1979, the average score reduced significantly to 29.59% which is just above chance given it is multiple choice with four potential answers. Around 25.5% of answers from those born after 1979 used the 'don't know' option in answering. Those born in the 1980's were shown famous figures from the 1960's and 1970's, around 10-20 years before they were born. Similarly, those born in the 1990's and 2000's were shown famous figures from the 1970's and 1980's, again 10-20 years before they were born, and this seemed to have a profound impact on their score. Those born in the 1950's were shown figures from the 2000's and 2010's, which is 20-30 years out with their reminiscence bump but still within their life span, but they scored almost 71%. Comparing this groups accuracy score to the younger group, there is a stark difference in accuracy score of almost 41%.

These results show an interesting pattern in the ability for people to remember famous figures from their life span, not just their reminiscence bump. This result and the difference in accuracy score by age group shows promise in the ability to estimate the age of an online user based on their accuracy score when identifying images of famous figures.

5.1 Research Questions

Returning to the initial research questions set out at the start of this paper:

RQ1: *How accurately can people identify famous figures from their reminiscence bump?*

RQ2:*How accurately can people identify famous figures from outside their reminiscence bump?*

The three studies show that there is a substantial difference in the accuracy rate where people are asked to identify people from outside their reminiscence bump. This translated into a 30% decline in accuracy overall, or a reduction by 48.09% for those born after 1979.

5.2 Ethics

5.2.1 Ethics Approval

Ethics approval was obtained from the University of Strathclyde Ethics Board, application number 2048. No personally identifiable information was collected and participants were reminded not to include any personal information within their survey responses. Any personal information collected through participants revealing it inadvertently was deleted as soon as possible.

6 Study Limitations

This research took an interactive approach where each study was adapted based on the findings of the previous, however, there are still a number of drawbacks which could have impacted the results.

6.1 Geography

Given the substantial work required to find suitable famous figures for each decade between 1960 and 2010, it was decided to keep the survey UK focused instead of trying to tailor this experiment for different geographies and cultures. This meant the survey could be focused to famous people British people will likely have seen on TV. A more global study would be needed to determine the viability of this method in real-world age assurance technologies.

6.2 N-Gram

N-Gram as a tool was a useful way of determining which famous figures to use, however, it does have several drawbacks. Due to the fact N-gram only shows statistics on the search term appearing in books, it may not be the best method to use if a famous figure has become popular on social media. Also, there may be a delay in books being published compared to when the famous figures may have appeared in mainstream media such as TV shows and movies. Similarly, N-Gram only has search terms up until 2019, meaning the most accurate information is not available for later decades.

6.3 Image Searching

During this survey, it would be possible for the participants to search online for the correct answer. However, to combat this, the final design of the system would include a time constraint to answer each question in order to minimise the time participants have to search online for the answer. The time constraint may add accessibility issues which would need to be further explored.

6.4 Participants

This study was carried out using adults only, and no children were tested. This does help to understand the images most adults can identify. It is presumed that this base lining method will allow the system to identify children more easily due to the fact their behaviour will likely be different to adults. There was a good age range across all three studies, however, 90% of participants described their ethnic origin as white which is not representative of the UK population. Future research should look to include better representation among other ethnics groups to align better with the UK population.

7 Conclusions and Future Work

This paper presents a study into whether the reminiscence bump can be used within a wider age assurance solution. The study investigated the accuracy scores of participants who were asked to identify famous figures from within and then outside their reminiscence bump. The results show there is indeed promise in utilising this psychological phenomena in a way that could help determine the age range of an online user without the need to identify them and thereby violate their privacy.

The feedback from participants after study 3 shows that this methodology provides a positive experience for the user while also allowing data to be collected which may help estimate their age.

This research must be combined with another technology solution to provide a more robust age assurance mechanism. By utilising Artificial Intelligence (AI), and potentially deception detection, it may be possible to develop The Nessa System, as an effective, affordable and privacy preserving online age assurance solution grounded in the findings reported in this paper. However, as with all AI, due care must be given to the development and use of this technology to ensure it is ethical and will not cause detriment to any online user [16].

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Appendix A

Table 8: Famous Figures used in Study 1 and Accuracy Score

Decade	Famous Figure	Accuracy Score
1960	Charles De Gaulle	80%
1960	Fidel Castro	100%
1960	Gamal Abdel Nasser	100%
1960	Indira Gandhi	100%
1960	Joan Baez	20%
1960	Nikita Khrushchev	80%
1970	Cesar Chavez	0%
1970	Chairman Mao	67%
1970	Che Guavara	83%
1970	Ellen Burstyn	0%
1970	Lyndon Johnson	38%
1970	Sidney Poitier	38%
1970	Willy Brandt	21%
1980	George H W Bush	75%
1980	Alan Alda	64%
1980	Diane Keaton	41%
1980	Jane Fonda	75%
1980	Ronald Reagan	98%
1980	Mikhail Gorbachev	91%
1980	Mary Tyler Moore	57%
1990	Burt Reynolds	27%
1990	Gary Synder	0%
1990	Jacqueline Kennedy Onassis	62%
1990	John Cleese	86%
1990	Richard Attenborough	14%
1990	Sonny Bono	0%
1990	Walt Disney	9%
2000	Lindsay Lohan	55%
2000	Billie Piper	70%
2000	Bob Geldof	60%
2000	Catherine Tate	70%
2000	Eddie Murphy	85%
2000	George Michael	65%
2000	Russell Crowe	75%
2010	Avril Lavigne	77%
2010	Barack Obama	100%
2010	Edward Snowden	31%
2010	Hilary Clinton	94%
2010	Hilary Duff	54%
2010	Rupert Murdoch	20%
2010	Steve Jobs	91%

Appendix B

Table 9: Famous Figures used in Study 2 and Accuracy Score

Decade	Famous Figure	Accuracy Score
1960	Charles De Gaulle	100%
1960	Fidel Castro	64%
1960	Gamal Abdel Nasser	64%
1960	Nikita Krushchev	64%
1960	Anna Karina	27%
1960	Yul Brynner	100%
1960	Charles Aznavour	82%
1970	Beatrice Arthur	21%
1970	Chairman Mao	67%
1970	Paul Michael Glaser	81%
1970	Mary Tyler Moore	91%
1970	Telly Savalas	100%
1970	Indira Gandhi	98%
1970	Jimmie Walker	11%
1980	Carol Burnett	65%
1980	Alan Alda	85%
1980	Jane Fonda	91%
1980	Loretta Swit	60%
1980	Ronald Reagan	99%
1980	Mikhail Gorbachev	99%
1980	Jaclyn Smith	84%
1990	Goldie Hawn	96%
1990	Demi Moore	80%
1990	Jacqueline Kennedy Onassis	94%
1990	Peter O'Toole	54%
1990	Prunella Scales	68%
1990	Patricia Routledge	87%
1990	Tom Selleck	94%
2000	Avril Lavigne	84%
2000	Hilary Duff	69%
2000	Bob Geldof	73%
2000	Catherine Tate	84%
2000	Janet Jackson	88%
2000	Lindsay Lohan	76%
2000	Russell Crowe	82%
2010	Billie Piper	67%
2010	Barack Obama	90%
2010	George Michael	75%
2010	Kylie Minogue	90%
2010	Ian Somerhalder	42%
2010	Kelly Brook	77%
2010	Steve Jobs	81%

Appendix C

Table 10: Study 3 - Decades shown by age and accuracy score

Decade born	Decades shown	Average Scores
<1950	1990's and 2000's	67.46%
1950-1959	2000's and 2010's	70.95%
1960-1969	1960's and 2010'	67.35%
1970-1979	1960's and 2010's	64.94%
1980-1989	1960's and 1970's	27.43%
1990-2004	1970's and 1980's	31.75%

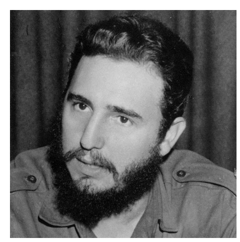
Appendix D - Photos Used

Table 11: 1960s Decade


Anna Karina


Charles De Gaulle


Charles Aznavour


Fidel Castro


Gamal Abdel Nasser


Nikita Khrushchev


Yul Brunner

Table 12: 1970s Decade

 Bea Arthur	 Mao Zedong	 Indira Ghandi	 Jimmie Walker
 Mary Tyler Moore	 Paul Michael Glaser	 Telly Savalas	

Table 13: 1980s Decade

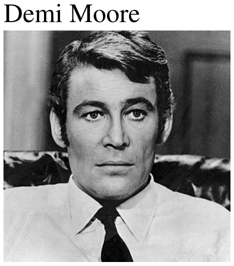
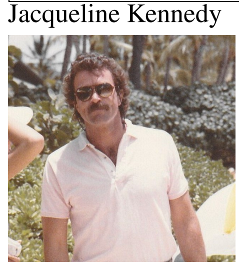
 Demi Moore	 Goldie Hawn	 Jacqueline Kennedy	 Patricia Routledge
 Peter O'Toole	 Prunella Scales	 Tom Selleck	

Table 14: 1990s Decade


Alan Alda


Carol Burnett


Jaclyn Smith


Mikhail Gorbachov


Jane Fonda


Ronald Reagan

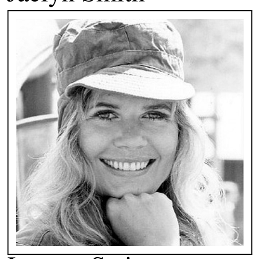
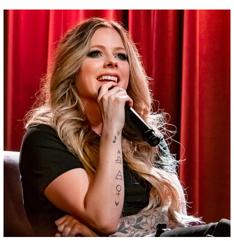
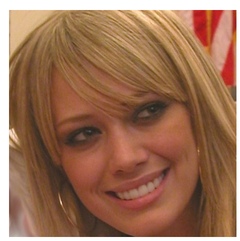

Loretta Swit

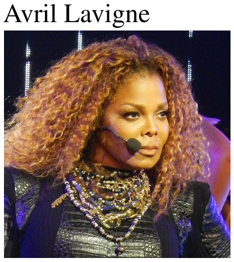
Table 15: 2000s Decade


Avril Lavigne


Bob Geldof


Catherine Tate


Hillary Duff


Janet Jackson


Lindsay Lohan

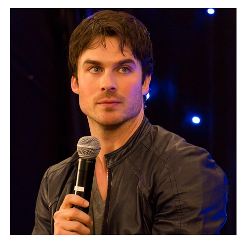

Russell Crowe

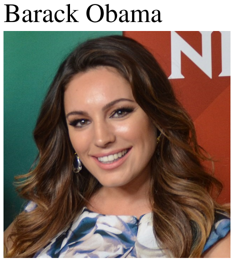
Table 16: 2010s Decade

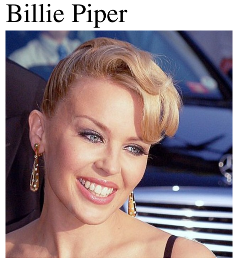

Barack Obama


Billie Piper


George Michael


Ian Somerhalder


Kelly Brook


Kylie Minogue


Steve Jobs