PSYCHOMETRIC PROPERTIES.

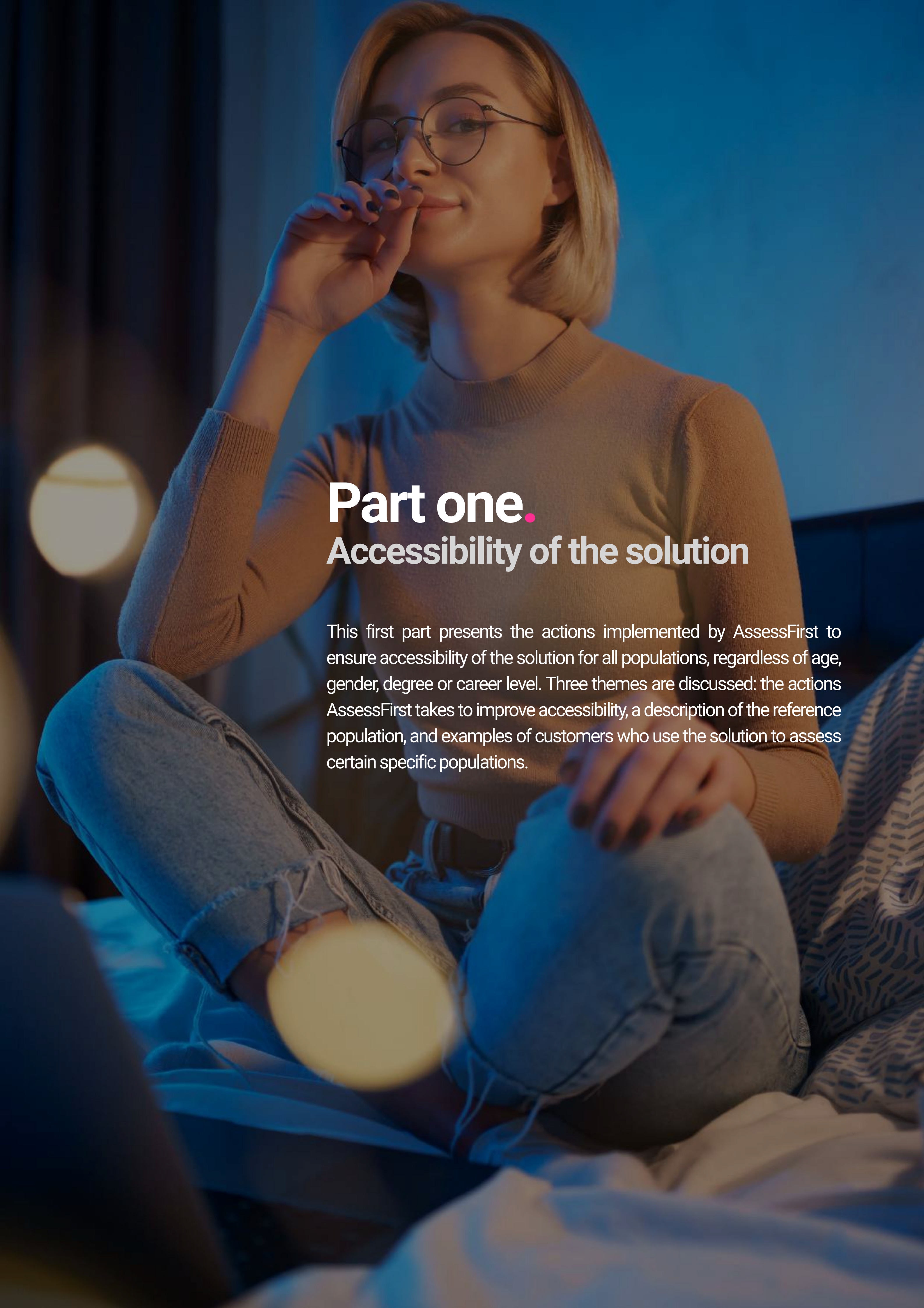
Accessibility and equity study of
the AssessFirst solution

ASSESSFIRST Study of accessibility and equity

This document contains information concerning the accessibility and equity of the AssessFirst solution (results of questionnaires and fit algorithm), notably when it comes to gender, age, disability or ethnic origin. Examples of client user stories are also presented throughout this document.

This document was written by the AssessFirst Science team.

CONTENTS.



Part one.

Accessibility of the solution

This first part presents the actions implemented by AssessFirst to ensure accessibility of the solution for all populations, regardless of age, gender, degree or career level. Three themes are discussed: the actions AssessFirst takes to improve accessibility, a description of the reference population, and examples of customers who use the solution to assess certain specific populations.

ACCESSIBILITY OF THE SOLUTION.

The user experience and accessibility of the solution are important issues of priority for AssessFirst. We therefore care about offering an assessment process and a results interface that are easy to use and understand. The efforts we deploy are what make AssessFirst an essential player when it comes to user experience today: the experience we offer is fluid, transparent, and above all, it addresses everyone, regardless of age, profession, degree, or mastery of digital tools, etc. The Google Reviews from solution candidates, available here, are a testimony to this.

AssessFirst is the uncontested leader on the market in terms of Candidate Experience and accessibility, **with a Google score of 4.9/5**, as shown here. This evaluation is the result of over 1832 reviews from candidates or recruiters using the solution.

Actions implemented.

The actions implemented by AssessFirst to ensure and improve accessibility of the solution include:

Professional nature of content

The questionnaires and results of the AssessFirst solution were specifically developed to be relevant in a professional context. The dimensions assessed were selected for their relevance to professional efficiency. The conclusions drawn from the use of AssessFirst are limited to this specific context.

Language level

AssessFirst relies on a Localization team made up of psychologists and experts in linguistic management, in order to provide textual content that is understandable and accessible to all, in all languages (15 languages currently available). We work with native-language translators to create and validate all of our content.

Validation of questionnaires

Personality-related questions (SHAPE) and motivation-related questions (DRIVE) were written in a way that requires no specific knowledge or level of education to understand. We also ensured that all responses given by respondents are not affected by factors such as age or gender.

Fairness by design

We build our questionnaires using neutral content, in that they make no references to cultural or social codes. For example, when it comes to reasoning, BRAIN exclusively solicits the use of primary logic (rotations, transformation, repetition, etc.) that is not affected by disabilities such as dyslexia or colorblindness. In this way, our tests offer the conditions for maximum success to all.

Text to speech

AssessFirst has developed our own text-to-speech tool to automatically read questionnaires. This feature provides access to a vocal assistant that reads the questions, reinforcing accessibility for people with visual disabilities.

Management of contrasts

AssessFirst implements actions to allow personalization of contrast and display settings of web content to make it easier to read for users with visual impairments.

Customer integration

Many partnerships have been implemented with target customers who offer the solution to populations who may have difficulty accessing the tool (e.g. users with disabilities, users with little access to employment, young populations, populations who lack digital literacy, populations without professional experience). Regular discussions with these partners and users allow us to continuously improve the solution in order to better meet their needs. Examples of these partnerships are provided in the remainder of the document.

Description of users.

To demonstrate the accessibility of the solution and its use by all types of populations, we propose here a description of a sampling of users that completed the questionnaires from 1 September 2020 to 1 September 2021. The description of this sample allows us to ensure that all populations are represented in terms of gender, age, level of education and level of career advancement.

Gender distribution:

	Total	Men	Women
Sample	466,537	47 %	53 %

The results in terms of gender distribution show no major discrepancy. Men and women are represented in almost identical proportions over the year studied.

Age distribution:

	Age category	Distribution
Sample	15-19	4.3%
	20-24	22.9%
	25-29	21.3%
	30-34	15.2%
	35-39	11.88%
	40-44	8.7%
	45-49	7.5%
	50-54	4.7%
	55-59	2.6%
	60-64	0.5%
	65-69	0.1%
	70	0.1%

The results in terms of distribution of age categories show that the ranges 20-24, 25-29, 30-34, 35-39, 40-44 and 45-49 are more proportionally represented than the "extreme" age categories. This distribution realistically reflects the heart of the activity of AssessFirst: our questionnaires are mainly used in the context of career decisions (orientation, recruiting, talent management). This implies that users of the solution are of working age. Also, these figures correspond to the data describing the working population presented by INSEE from 2014 to 2020: the age range 25 to 49 years old being the range with the most working people and which presents the highest level of career mobility (study by Deloitte, 2015).

Distribution of education levels:

	Degree	**Total**
Sample	Doctorate / PhD	1.3%
	Master	32.4%
	Bachelor	36.0%
	High school diploma	16.5%
	Vocational diploma	9.7%
	None	4.2%

The results in terms of distribution for level of education show a slight over-representation of users with a Bachelor's or Master's degree. There are 2 main reasons for this over-representation: (1) The natural and increasing representativity of people with a tertiary level of education in the population - around 50% according to figures from the OECD from 2017 to 2020, and (2), the slightly more prevalent use of the solution by our clients to recruit managerial-level profiles.

Distribution of responsibility levels:

	Level of responsibility	**Total**
Sample	Associate	1.5%
	Vice president	0.1%
	Executive management	1.4%
	Director	5.9%
	Manager	12.2%
	Experienced	38.6%
	Recent graduate	22.4%
	Internship	9.3%
	Not applicable	8.5%
	Volunteer	0.2%

The figures presented allow us to ensure representativeness of the population for use of the AssessFirst service. Therefore, all genders, ages, degrees and career levels are represented among our users. And while slight differences may exist (over-representation or under-representation), they are mostly inherent to the natural specificities of the working population.

Client user stories.

Many of our clients use AssessFirst to recruit or support specific or so-called "sensitive" employee profiles. The examples provided by our clients allow us to: (1) reinforce our capacity to access qualitative and quantitative feedback in order to continuously improve our solution, and (2) demonstrate the accessibility of our solution to all populations.

Schools using the solution

Many schools use AssessFirst for student orientation and guidance. Our solid partnerships with these schools therefore allow us to demonstrate the capacity of the solution to address a "non-professional" public that has not yet officially accessed employment.

Organizations with social impact

AssessFirst has also built many solid partnerships with organizations who have a social impact. These organizations use the solution to hire, reorient or guide sectors of the population that are in difficulty, such as: people who lack access to employment, people recently released from prison, people of ethnic minorities, people who do not have an education.

Partnership with French "Pôle emploi"

"Boost your professional image"

En In 2018, the French unemployment office « Pôle emploi » launched a service to accompany job seekers in the development of their professional attitude and presence in order to facilitate their recruitment and re-integration to the professional world. After responding to a call for tenders, AssessFirst was selected to carry out this project, entitled, "Boost your professional image" (Original name: *Valoriser son image professionnelle*). Our assessment solution is now used by job seekers to evaluate their professional attitudes and measure their progress. The project started in 2019 and was renewed in 2022. **A total of more than 224,858 job seekers** (profiles with little access to employment over several years - long-term unemployed, young people and those not integrated in the professional world, profiles without degrees or diplomas, etc.) have completed the AssessFirst questionnaires. This program and the questionnaires proposed by AssessFirst have received very positive feedback and praise from job seekers. Evaluations are available in the Google Reviews provided here.

Survey of job seekers.

As part of another collaboration with the unemployment office in early 2022, we also had the opportunity to measure the satisfaction of job seekers when it comes to using our solution and accessibility of the questionnaires. This survey was carried out rom 1 February 2022 to 8 April 2022 with 180 job seekers who had completed the 3 AssessFirst questionnaires:

- 96% gave a positive opinion on the service (average score of 8.5/10);

- 90% found the results easy to understand (8.5/10);
- 98% found the questionnaires easy to use (9.3/10);
- 98% found the results and the solution useful (8.4/10).

These results were obtained from populations receiving specific guidance, such as: about 70% of job seekers with a high school diploma level or lower, or an intensive guidance program for youth.

Section conclusion.

This first part demonstrates the accessibility of the AssessFirst solution. This is an absolute priority at AssessFirst: making sure each individual can benefit from their results in order to better understand what makes them unique and therefore highlight their talents. Today, the results we obtain from our partners make AssessFirst one of the most innovative and most inclusive companies in HR Tech. We have impacted the life trajectory of more than 5,000,000 people. 5,000,000 individuals who have had the opportunity to be considered for who they really are as human beings, beyond their academic path, professional experience, age or gender. This is what the results here show: they support the quality of the user experience for all populations.

Part two.

Equity in the questionnaires results

This second part covers the question of equity in the results to the questionnaires on personality (SHAPE), motivations (DRIVE) and reasoning (BRAIN). The results and potential differences between groups are presented according to 4 variables of analysis: user gender, age, disability, and ethnic origin.

EQUITY IN THE QUESTIONNAIRES RESULTS.

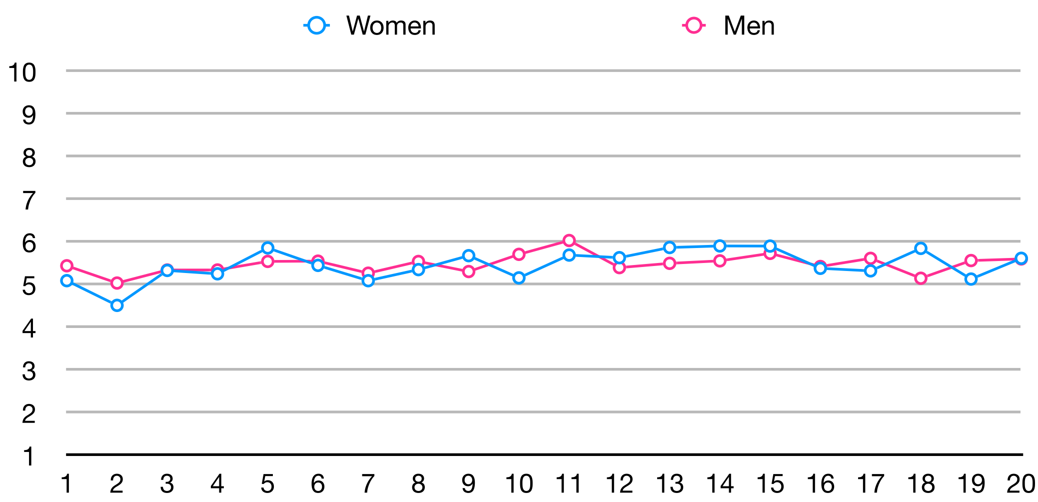
The data presented in this section demonstrates that there are no significant differences, or any differences with a major impact, in the results of the SHAPE, DRIVE and BRAIN questionnaires according to variables of gender, age, disability or ethnic origin. Note: only the personal information necessary for correct use of the AssessFirst solution are requested from users. For example, there is no mention of religion, politics or sexual orientation at any time. When it comes to age, we ask for the user's date of birth to ensure it does not affect the way the questions are processed. **Similarly, none of the variables analyzed here (gender, age, disability, ethnic origin) ever intervene in the calculation of results in the solution.**

Gender equity.

Description of the sample used for gender analysis:

Total	Men	Women
332,587	51 %	49 %

Average scores for the 20 SHAPE dimensions according to gender:

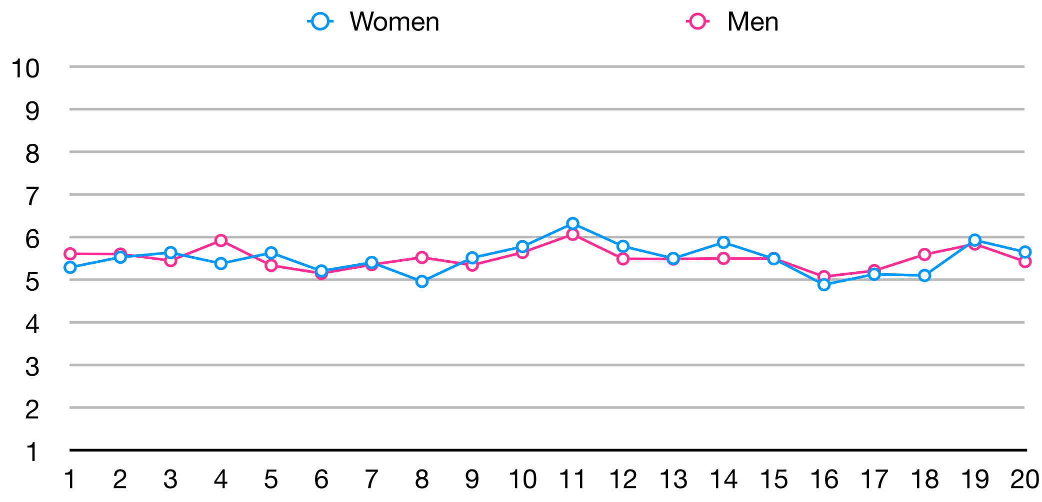


To measure the effect - or lack thereof - of gender on questionnaire results, we used Cohen's *d* statistic. Cohen's *d* is a popular measurement used in psychology to characterize the effect size associated with a given population in relation to a null hypothesis of equality of statistical parameters. Generally, a value d ≈ 0.0 indicates that there is no effect, a value of d ≈ .3 corresponds to a small effect, d ≈ 0.5 corresponds to a medium effect and d ≈ 0.8 corresponds to a large effect.

The most salient effects are on dimensions 3 (approaches others spontaneously, *d* = .27), 10 (is interested in abstract ideas, *d* = .28) and 18 (focuses on the positive, *d* = - .26). However, **these effects are below .3, and are therefore very weak.**

The averages obtained on the 20 dimensions are situated around the theoretical average of 5.5. There is no major difference between the results of men and women across the 20 dimensions measured by SHAPE. Results are thus gender-equitable.

Average scores for the 20 DRIVE dimensions according to gender:



The most salient effects are on dimensions 4 (analyse data, *d* = .26), 10 (having influence, *d* = .28) and 18 (seeks competition, *d* = .26). However, **these effects are below .3, and are therefore very weak.**

The averages obtained on the 20 dimensions are situated around the theoretical average of 5.5. There is no major difference between the results of men and women across the 20 dimensions measured by DRIVE. Results are thus gender-equitable.

Average scores for BRAIN according to gender:

Dimension	Men	Women
Global score (out of 10)	5.74	5.59
Time (out of 10)	60.98	58.90

The averages on the overall BRAIN score are both around the theoretical average of 5.5. There is no major difference between the results of men and women across the two dimensions measured by the reasoning questionnaire.

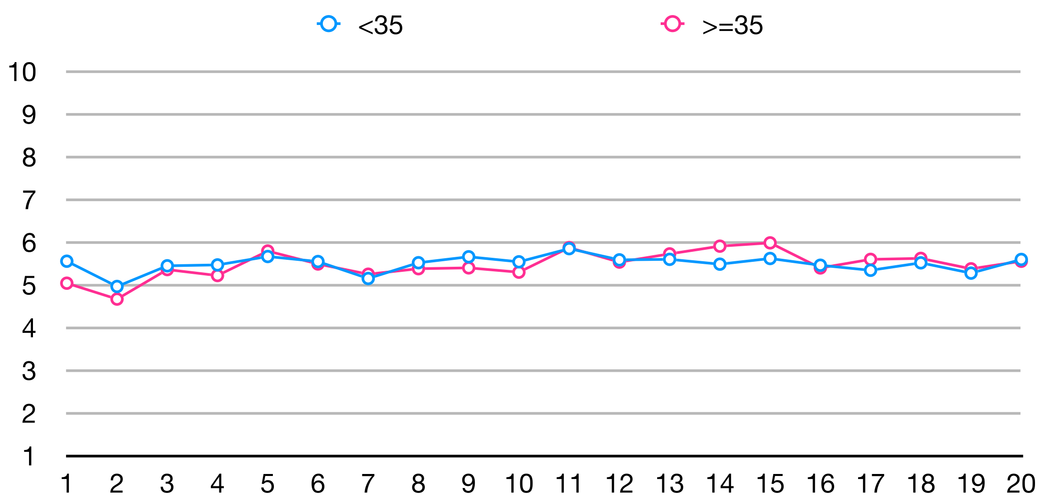
Age equity.

Description of the sample used for age analysis:

Total	Under 35 years old	Over 35 years old
64,675	42 %	58 %

Note: to compare the results, we split the sample into two age groups starting from the age of 35 (due to the average age of the sample, which is 33.3 years old - with a standard deviation of 10.2 years).

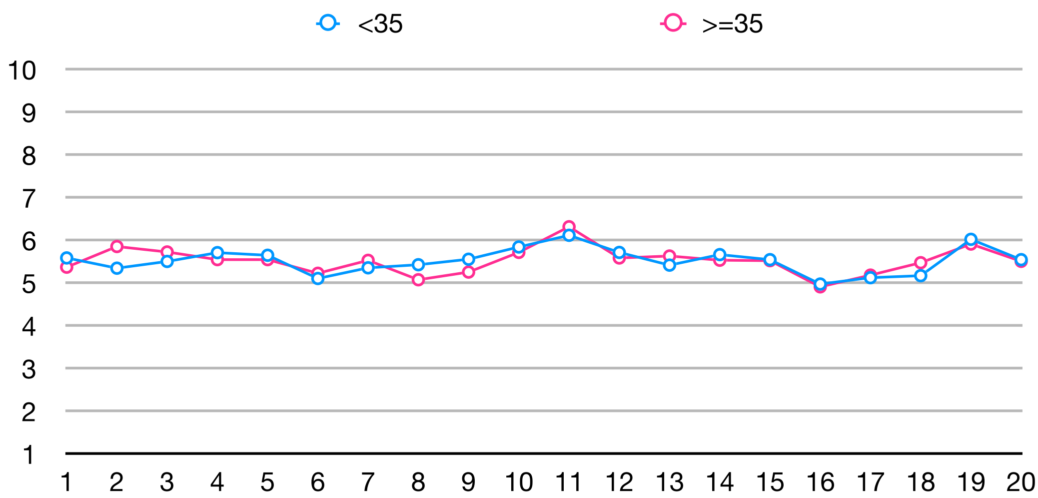
Average scores for the 20 SHAPE dimensions according to age:



The most salient effect is on dimension 1 (is assertive with others, *d* = .26). However, **this effect is below .3, and are therefore very weak.**

The averages obtained on the 20 dimensions are situated around the theoretical average of 5.5. There are no major differences between the results of people under 35 years old, and those over 35 years old.

Average scores for the 20 DRIVE dimensions according to age:



The most salient effect is on dimension 2 (excelling everyday, *d* = .25). However, **this effect is below .3, and is therefore very weak.**

The averages obtained on the 20 dimensions are situated around the theoretical average of 5.5. There are no major differences between the results of people under 35 years old, and those over 35 years old.

Ethnic origin equity.

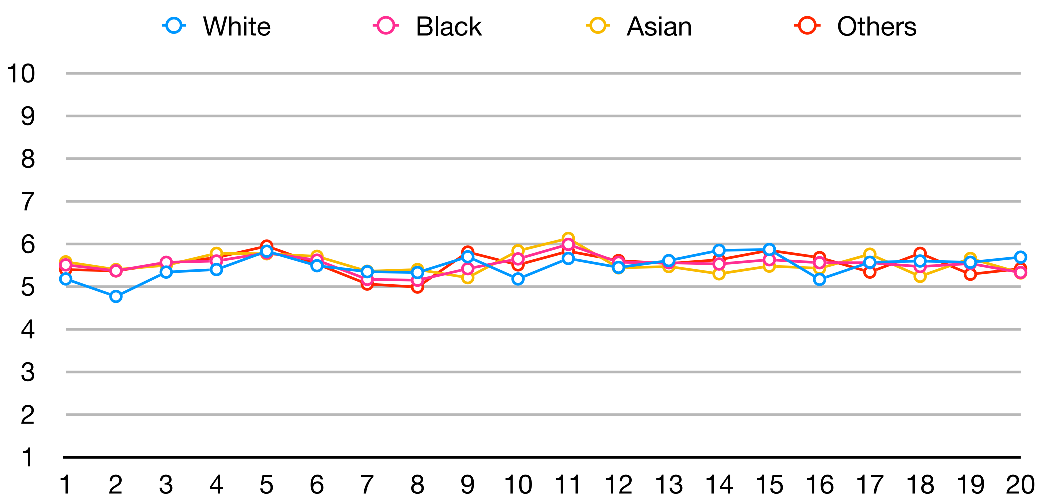
Due to French law, we are not authorized to collect information relating to ethnic origin of users in many countries: we therefore do not collect this data continuously or regularly. As a result, the analyses presented below, while reliable, must be considered with caution due to the relatively small sample size, **restricted to users located in the United States and the United Kingdom**.

Similarly, we cannot provide sufficient data for all existing ethnic origins. Ethnic origins for which the sample sizes are insufficient were grouped into a single category labeled, “Other”. This category includes the following ethnic origins: American Indian, Chinese, Hispanic, MENA (Middle East and North Africa), Pacific Islander, and two or more ethnic origins.

Description of the sample used for analysis of ethnic origin:

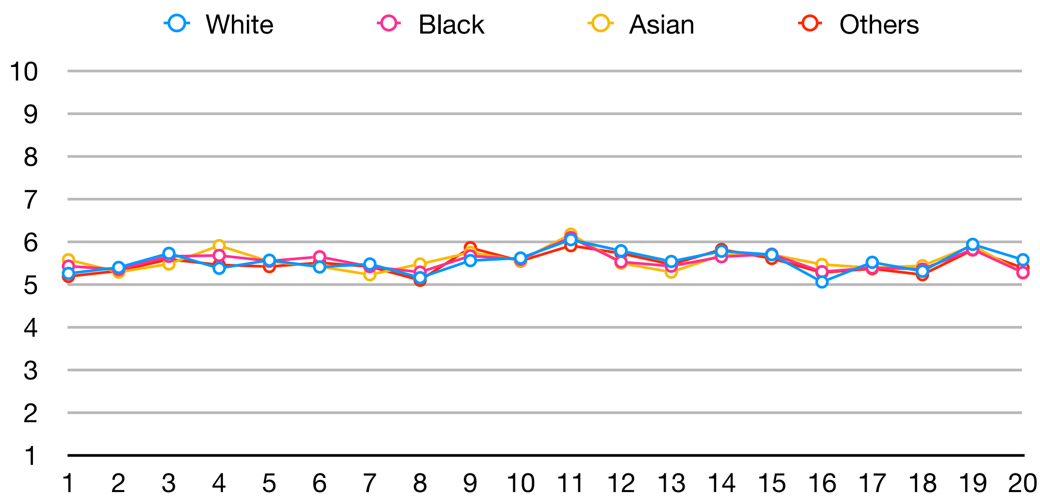
Total	White	Black	Asian	Others
1515	59.5% (901)	11.1% (168)	15.1% (228)	14.4% (218)

Average scores for the 20 SHAPE dimensions according to ethnic origin:



The averages obtained on the 20 dimensions are situated around the theoretical average of 5.5 for each group in the study. There are no major differences in people's results according to their ethnic origin.

Average scores for the 20 DRIVE dimensions according to ethnic origin:



The averages obtained on the 20 dimensions are situated around the theoretical average of 5.5 for each group in the study. There are no major differences in people's results according to their ethnic origin.

Average scores for BRAIN according to ethnic origin:

Dimension	White	Black	Asian	Others
Global score (out of 10)	5.74	5.56	5.60	5.49
Time (out of 10)	57.42	64.27	62.15	63.17

The averages on the overall BRAIN score are all around the theoretical average of 5.5. There are no major differences in people's BRAIN results according to their ethnic origin.

Disability equity.

Due to the sensitive nature of this data, we only collect it on certain occasions, anonymously, and as part of impact studies. The analyses presented below could be carried out on a rather large sample of people with a disability (N = 2972).

Note that different types of disabilities were considered, i.e. mental (N = 374), auditory (N = 279), visual (N = 176), physical (N = 303), autistic disorder (N = 55), dyslexia (N = 464), dyscalculia (N = 46), cognitive disorders (N = 35), ADHD and other attention disorders (N = 144), and other types of disabilities (N = 1096).

To prevent the effects that can result from small sample sizes for certain types of disability, the study below groups together all people with a disability under the label "with disability" (total N = 2972).

To measure the effect - or lack thereof - of disability on questionnaire results, we used Cohen's *d* statistic. Cohen's *d* is a popular measurement used in psychology to characterize the effect size associated with a given population in relation to a null hypothesis of equality of statistical parameters. Generally, a value $d \approx 0.0$ indicates that there is no effect, a value of $d \approx .3$ corresponds to a small effect, $d \approx 0.5$ corresponds to a medium effect and $d \approx 0.8$ corresponds to a large effect. In this study, we needed to ensure there was not a medium or large effect between the two groups "without disability" and "with disability".
The table below summarizes the effect sizes for the 20 dimensions of SHAPE, according to the presence or absence of disability:

Dimension No.	Average without disability	Average with disability	Cohen's *d* value	Effect size
1	5.22	4.86	0.184	Very small
2	4.74	4.63	0.057	-
3	5.37	5.39	0.014	-
4	5.27	5.33	0.03	-
5	5.72	6.15	0.224	Very small
6	5.55	5.59	0.027	-
7	5.15	5.34	0.105	-
8	5.47	5.43	0.025	-
9	5.45	5.55	0.055	-
10	5.45	4.95	0.255	Very small
11	5.87	5.80	0.037	-
12	5.58	5.42	0.086	-
13	5.74	5.40	0.175	-
14	5.75	5.91	0.082	-
15	5.82	5.84	0.014	-
16	5.47	5.13	0.171	-
17	5.50	5.38	0.059	-
18	5.56	5.50	0.029	-
19	5.31	5.46	0.079	-
20	5.58	5.87	0.161	-

For 17 dimensions out of 20, the presence of a disability does not have an effect on the scores: on these 17 dimensions, the people with disabilities have nearly identical results to people without disabilities. For 3 dimensions ("leads and is assertive with others" - 1, "connects emotionally" - 5, and "is interested in abstract ideas" - 10), there are very small effect sizes. People with a disability have slightly lower scores on dimensions 1 and 10 and higher scores on dimension 5. However, it should be noted that: (1) these effects are rare - 3 dimensions out of 20, (2) these effects are very small, and, (3) they are potentially inherent to an affect of the sample and the academic degree level: there is an imbalance in representativeness in terms of degree level between the two groups - more masters and doctorate degrees in the group without disabilities. Also, additional analyses demonstrate that similar effects occur on the same 3 dimensions, but when we look at degree level and not disability.

The table below summarizes the effect sizes for the 20 dimensions of DRIVE, according to the presence or absence of disability:

Dimension No.	Average without disability	Average with disability	Cohen's *d* value	Effect size
1	5.53	5.23	0.15	-
2	5.74	5.12	0.312	Small
3	5.53	5.86	0.16	-
4	5.77	5.35	0.212	Very small
5	5.61	5.46	0.077	-
6	5.11	5.31	0.101	-
7	5.48	5.32	0.08	-
8	5.29	4.75	0.279	-
9	5.32	5.68	0.181	Very small
10	5.89	5.46	0.206	Very small
11	6.31	6.18	0.063	-
12	5.60	6.02	0.216	Very small
13	5.54	5.74	0.101	-
14	5.49	6.18	0.343	Small
15	5.40	5.88	0.237	Very small
16	4.87	5.01	0.066	-
17	4.96	5.38	0.195	Very small
18	5.39	5.08	0.173	Very small
19	5.99	6.10	0.05	-
20	5.55	5.62	0.039	-

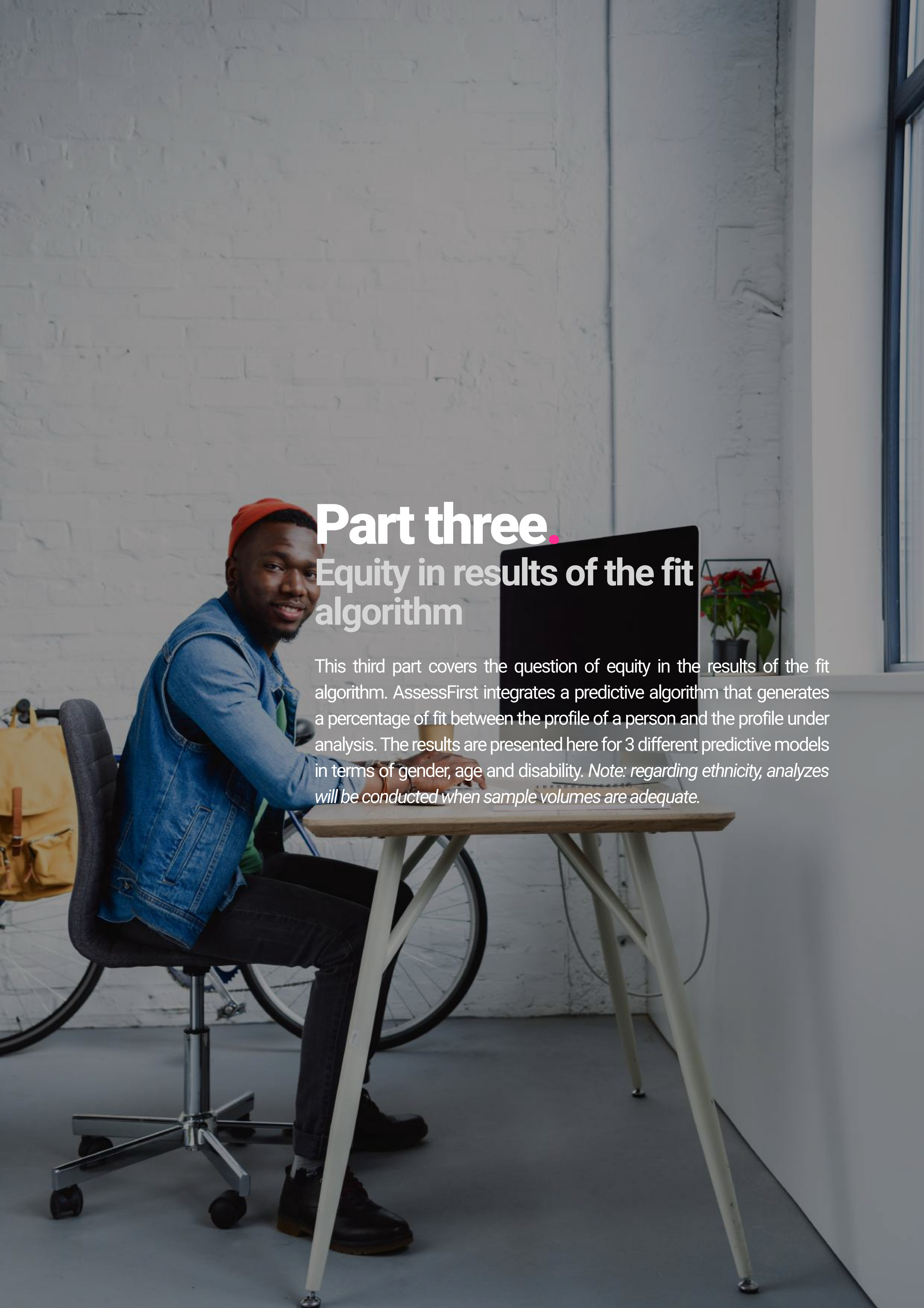
For 11 dimensions out of 20, the presence of a disability does not have an affect on scores: on these 11 dimensions, people with a disability have almost identical results to people without disabilities. For 9 dimensions ("excelling every day" - 2, "analyzing data" - 4, "having autonomy" - 9, "working as part of a team" - 10, "working in a fun environment" - 12, "maintaining personal balance" - 14, "working in a disciplined manner" - 15, "having an attractive remuneration" - 17, and "seeks competition" - 18), there are very small or small effect sizes. People with a disability have slightly lower scores on dimensions 2, 4, 10, and 18 and higher scores on dimensions 9, 12, 15 and 17. However, it should be noted that: (1) these effects are mostly very small and, (2) they are potentially inherent to an effect of the sample and the degree level: there is an imbalance in representativeness in terms of degree level between the two groups - more masters and doctorate degrees in the group without disabilities. Also, additional analyses demonstrate that similar effects occur on 5 of the concerned dimensions, but when we look at degree level and not disability.

The table below summarizes the effect sizes for the overall BRAIN score, according to the presence or absence of disabilities:

Dimension No.	Average without disability	Average with disability	Cohen's *d* value	Effect size
33	5.59	4.95	0.3	Small

Section conclusion.

Whether in terms of gender, age, ethnic origin or disability, there are no major differences in the results obtained by the various groups responding to the AssessFirst SHAPE, DRIVE and BRAIN questionnaires. In short, the results obtained allow us to support the hypotheses that the questionnaires proposed do not discriminate against any one population and are equitable. The most marked effects concern disabilities (notably mental and cognitive disabilities) - even if the effects mentioned are very small or small and can be explained by other interactions.



Part three.

Equity in results of the fit algorithm

This third part covers the question of equity in the results of the fit algorithm. AssessFirst integrates a predictive algorithm that generates a percentage of fit between the profile of a person and the profile under analysis. The results are presented here for 3 different predictive models in terms of gender, age and disability. *Note: regarding ethnicity, analyzes will be conducted when sample volumes are adequate.*

EQUITY IN THE ALGORITHM RESULTS.

Preamble.

Modeling of expectations

The questionnaires proposed by AssessFirst allow us to assess the personality and motivations of a person. However, it's one thing for an assessment to be designed as fair and valid, but how it is used is an entirely other thing. To limit subjectivity bias related to the analysis of results, AssessFirst provides users with predictive models. These models allow us to perform matching and calculate a fit score between the profile of a person and a mission. The predictive models are reading grids associated with a profession or particular function. There are three different types of predictive models:

- **Benchmark predictive models:** a model based on the data collected from all questions filled out for AssessFirst. These models allow us to identify to what extent a candidate shares the characteristics of people performing a certain job. Only the statistical dimensions representative of the population studied are retained.

- **Personalized predictive models:** with these models, users are able to select the dimensions integrated in the model themselves. This process allows us to check that the dimensions present in the model are selected to encourage professional efficiency in the specific conditions chosen.

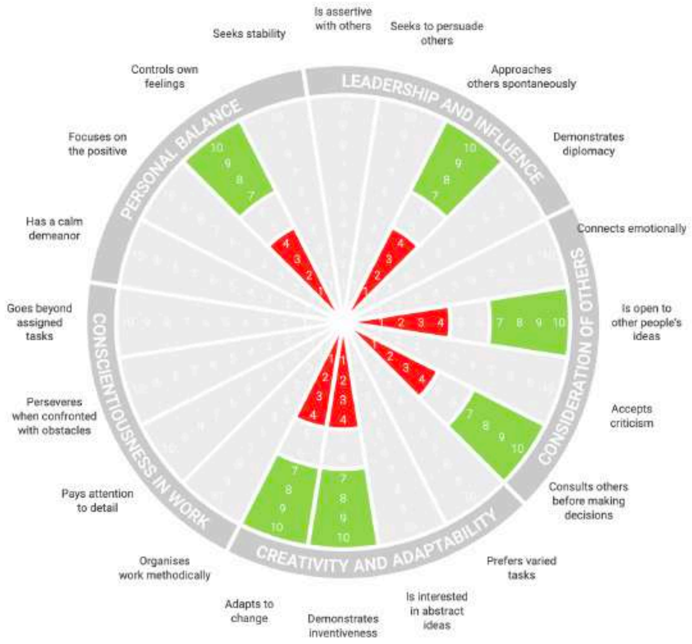
- **Talent Review models:** this type of model is the most precise technique AssessFirst has developed to ensure maximum equity in the assessment process. People currently in a position in the same company are assessed and characteristics that significantly influence performance are isolated.

Example of predictive model

To better understand the modeling of expectations, and the transition between the baseline and the final model, a summarized example is attached here, recently performed with one of our clients.

Client required skills	Corresponding dimensions	Expected scores
Collaboration and teamwork	Shows interest in others' ideas (SHAPE)	7-10
	Consults others before making decisions (SHAPE)	7-10
	Working as part of a team (DRIVE)	7-10
Developing relationships	Approaches others spontaneously (SHAPE)	7-10
	Controls own feelings (SHAPE)	1-4
	Meeting new people (DRIVE)	7-10
Creativity and innovation	Demonstrates inventiveness (SHAPE)	7-10
	Adapts to change (SHAPE)	7-10
	Creating new things (DRIVE)	7-10

How should we understand this? Each skill is associated with a certain number of corresponding SHAPE/DRIVE dimensions. The combination of these dimensions constitutes the model we'll use to measure the potential on a target skill. For example, a model with the dimensions, "shows interest in others' ideas", "consults others before making decisions" and "working as part of a team", allow us to measure the candidate's potential on the "collaboration and teamwork" skill.



Calculation of fit

The AssessFirst solution automatically calculates the rate of fit between the candidate and the predictive model. This overall fit is presented as a percentage between 0 and 100%. It indicates a candidate's potential for success on the mission in question.

Grid for interpreting levels of fit:

Fit	Interpretation
From 60% to 100%	High potential for success: the candidate presents most of the motivations and personality traits required.
From 40% to 59%	Zone of uncertainty: this means the candidate has an equal probability (about 50%) of succeeding or failing when faced with the expectations of the position.
From 0% to 39%	Low potential for success. The candidate's profile does not correspond to the expected characteristics.

An approach without bias

The rigor of our methodology and our expertise allow us to neutralize the potential bias at each step of our process:

- **The psychometric qualities** of our questionnaires demonstrate the absence of bias in the assessment. Our Science team ensures the scientific robustness of the questionnaires and is an affiliated member of the ITC (International Test Commission), a reference when it comes to standards for developing assessment tools.

- **When predictive models** are created based on the "human" translation of a skill baseline, the most common biases are related to individual intuition and idiosyncratic projections of the creator. To neutralize these potential biases: (1) we follow a proven work methodology, based on a deep analysis of the mission, specifically angled on the personality; (2) model creation is assigned to a group; (3) the group is functionally diversified; (4) this work is carried out according to solid baselines that have psychological authority.

- **The fit calculation** is based solely on a numerical algorithm that only takes into account the criteria of personality and motivation selected in the model.

Study of algorithm equity.

To ensure equitable use of the algorithm, we recently carried out new studies on three predictive models for three different professions in terms of role and level of responsibility: (1) project manager, (2) customer advisor, and (3) qualified technician. These 3 professions were selected for their diversity, but also because they correspond to three professions for which one of our clients (referred to as C-ONE, here), provided us with detailed job descriptions.

The studies are based on the analysis of gender, age and disability representativeness in the profiles recommended (profiles with fit above 60%), or not recommended (profiles with fit below 40%). In summary, to ensure that the use of the algorithm is not discriminatory:

- The proportion of men and women recommended or not recommended by the algorithm (system output), must globally be the same as the proportion of men and women at system input;
- The proportion of different ages among the people recommended or not recommended by the algorithm (system output), must globally be the same as the proportion of different ages at system input.
- The proportion of people with, and without disability, recommended by the algorithm (system output), must globally be the same as the proportion of people with a disability and people without a disability at system input.

The studies for the 3 target professions are presented below.

Project manager

The mission of the project manager, as defined for this project and by the C-ONE company, is as follows: "*manage one or more projects from initialization up to completion with the objective of obtaining an optimal result that complies with the customer objectives and requirements*."

The first step of the work consists in creating the predictive model. This model was built by a team of 3 expert psychologists, based on a translation of the C-ONE job description into the personality and motivation baseline of AssessFirst.

The dimensions integrated in the model are presented in the table below:

Questionnaire	Corresponding dimensions
SHAPE Personality	Leads and is assertive with others
	Shows interest in others' ideas
	Accepts criticism
	Preference for varied tasks
	Adapts to change
	Organizes work methodically
	Perseveres when confronted with obstacles
	Focuses on the positive
	Controls own feelings
	Demonstrates responsiveness
DRIVE Motivations	Excelling every day
	Analyzing data
	Meeting new people
	Focusing on quality
	Having influence
	Having autonomy
	Devoting themselves to their career
	Helping others
	Being recognized by others

First analysis.

A first analysis of model equity was carried out, taking into consideration a general population. The distribution in terms of gender, age and disability are shown in the tables below.

Gender sample	Total	Men	Women
Global	374,841	188,351 (50%)	186,490 (50%)

Note: to ensure fair use, the algorithm should therefore recommend men and women in approximately 50/50 proportions (profile fit greater than or equal to 60%). The reasoning is the same for profiles that are not recommended (fit below 40%).

Age sample	Total	Age category	Distribution
Global	23,584	18-25	6461 (27%)
		26-35	8492 (36%)
		36-45	5026 (21%)
		46 and over	3605 (15%)

Note: to ensure fair use, the algorithm should therefore recommend people according to a very similar distribution by age. About 27% of 18-25 year-olds, 36% of 26-35 year-olds, 21% of 36-45 year-olds, and 15% of people 46 and over.

Disability sample	Total	Avec handicap	Sans handicap
Global	27,958	2229 (8%)	25,729 (92%)

Note : to ensure fair use, the algorithm should therefore recommend people with disability and people without disability on approximately 8/92 proportions (profile fit greater than or equal to 60%). The reasoning is the same for profiles that are not recommended (fit below 40%).

Results of the gender analysis:

Fit	Men	Women
0 to 39%	21,488 (11%)	20,273 (11%)
40 to 49%	69,931 (37%)	70,402 (38%)
50 to 59%	76,712 (41%)	74,845 (40%)
60 to 100%	20,220 (11%)	20,970 (11%)

The algorithm recommends (fit above 60%) 20,220 men and 20,970 women - i.e. 41,190 people total, 49% of whom are men and 51% of whom are women. Similarly, the algorithm does not recommend (fit below 40%) 21,488 men and 20,273 women - i.e. 41,761 people total, 51% of whom are men and 49% of whom are women.

In conclusion, the algorithm recommends - and does not recommend - profiles of men and women in very similar proportions to the distribution of the sample used (50% men and 50% women). Use of the algorithm can therefore be considered equitable and non-discriminatory in terms of gender.

Also, the study of Cohen's *d* statistic on the fit averages of men and women ensures the equity and non-discrimination of algorithm use between the two groups:

Average of men	Average of women	Cohen's *d* value	Effect size
49.80	49.97	0.022	No effect

Results of the age analysis:

Fit	18-25	26-35	36-45	46 and over
0 to 39%	784 (12%)	939 (11%)	500 (10%)	338 (9%)
40 to 49%	2464 (38%)	3176 (37%)	1819 (36%)	1270 (35%)
50 to 59%	2587 (40%)	3458 (41%)	2133 (42%)	1535 (43%)
60 to 100%	626 (10%)	919 (11%)	574 (11%)	462 (13%)

The algorithm recommends (fit above 60%) 626 people ages 18-25, 919 people ages 26-35, 574 people ages 36-45, and 462 people age 46 and over. That is 2581 people total, 24% of whom are ages 18-25, 36% ages 26-35, 22% ages 36-45, and 18% age 46 and over. The algorithm does not recommend (fit below 40%) 784 people ages 18-25, 939 people ages 26-35, 500 people ages 36-45, and 338 people age 46 and over. That is 2561 people total, 30% of whom are ages 18-25, 36% ages 26-35, 19% ages 36-45, and 13% age 46 and over.

In conclusion, the algorithm recommends and does not recommend profiles in very similar proportions as that of the sample distribution used in terms of age (27% ages 18-25, 36% ages 26-35, 21% ages 36-45, and 15% age 46 and over). Use of the algorithm can therefore be considered equitable and non-discriminatory in terms of age.

Also, the study of Cohen's *d* statistic on the fit averages of each group ensures the equity and non-discrimination of algorithm use among the various groups. To manage this analysis 2 by 2, each group is compared to a second group that integrates all of the other age classes.

Average of the 18-25 year old group	Average of the other groups	Cohen's *d* value	Effect size
49.49	50.13	-0.08	No effect

Average of the 26-35 year old group	Average of the other groups	Cohen's *d* value	Effect size
49.84	50.02	-0.02	No effect

Average of the 36-45 year old group	Average of the other groups	Cohen's *d* value	Effect size
50.21	49.89	0.04	No effect

Average of the 46 and over group	Average of the other groups	Cohen's *d* value	Effect size
50.62	49.84	0.1	No effect

Results of the disability analysis:

Fit	With disability	Without disability
0 to 39%	343 (15%)	2399 (9%)
40 to 49%	915 (41%)	9183 (36%)
50 to 59%	792 (35%)	10,997 (42%)
60 to 100%	179 (8%)	3150 (12%)

The algorithm recommends (fit above 60%) 179 persons with a disability and 3150 persons without a disability - i.e. 3329 people total, 5% of whom are people with a disability and 95% of whom are people without a disability. Similarly, the algorithm does not recommend (fit below 40%) 343 persons with a disability and 2399 persons without a disability - i.e. 2749 people total, 12% of whom are people with a disability and 88% of whom are people without a disability.

In conclusion, the algorithm recommends - and does not recommend - profiles of people with a disability and people without a disability in very similar proportions to the distribution of the sample used (8% of people with a disability and 92% of people without a disability). Use of the algorithm can therefore be considered equitable and non-discriminatory in terms of disability.

Also, the study of Cohen's *d* statistic on the fit averages of people with a disability and people without a disability ensures the equity and non-discrimination of algorithm use between the two groups. The effect is indeed very small, and the means of the two groups are almost similar.

Mean with a disability	Mean without a disability	Cohen's *d* value	Effect size
48.35	50.54	0.28	Very weak

The results presented in this first analysis validate the non-discrimination and equity in use of the algorithm: the algorithm recommends profiles in almost identical proportions as the proportions at process input, according to gender and age.

Second analysis.

A second analysis of model equity was carried out, taking into consideration a specific population of project managers. The distribution in terms of gender and age are shown in the tables below. *Note: Disability-related studies cannot be conducted with a specific sample due to the low number of people who register on the application indicating that they are project managers and have a disability.*

Gender sample	Total	Men	Women
Specific	17,511	10,806 (62%)	6705 (38%)

Note: to ensure fair use, the algorithm should therefore recommend men and women in approximately 62/38 proportions (profile fit greater than or equal to 60%). The reasoning is the same for profiles that are not recommended (fit below 40%).

Age sample	Total	Age category	Distribution
Specific	3774	18-25	303 (8%)
		26-35	1582 (42%)
		36-45	1192 (32%)
		46 and over	697 (19%)

Note: to ensure fair use, the algorithm should therefore recommend people according to a very similar distribution by age. About 8% of 18-25 year-olds, 42% of 26-35 year-olds, 32% of 36-45 year-olds, and 19% of people 46 and over.

Results of the gender analysis:

Fit	Men	Women
0 to 39%	934 (9%)	465 (7%)
40 to 49%	3513 (33%)	2273 (34%)
50 to 59%	4721 (44%)	2907 (43%)
60 to 100%	1638 (15%)	1060 (16%)

The algorithm recommends (fit above 60%) 1638 men and 1060 women - i.e. 2698 people total, 61% of whom are men and 39% of whom are women. Similarly, the algorithm does not recommend (fit below 40%) 934 men and 465 women - i.e. 1399 people total, 66% of whom are men and 33% of whom are women.

In conclusion, the algorithm recommends - and does not recommend, profiles of men and women in very similar proportions to the distribution of the sample used (62% men and 38% women). Use of the algorithm can therefore be considered equitable and non-discriminatory in terms of gender.

Also, the study of Cohen’s *d* statistic on the fit averages of men and women ensures the equity and non-discrimination of algorithm use between the two groups:

Average of men	Average of women	Cohen’s *d* value	Effect size
51.37	51.57	0.027	No effect

Results of the age analysis:

Fit	18-25	26-35	36-45	46 and over
0 to 39%	25 (8%)	129 (8%)	73 (6%)	45 (6%)
40 to 49%	112 (37%)	511 (32%)	381 (32%)	213 (31%)
50 to 59%	116 (38%)	683 (43%)	550 (46%)	319 (46%)
60 to 100%	50 (16%)	259 (16%)	188 (16%)	120 (17%)

The algorithm recommends (fit above 60%) 50 people ages 18-25, 259 people ages 26-35, 188 people ages 36-45, and 120 people age 46 and over. i.e. 617 people total, with 8% of 18-25 year-olds, 42% of 26-35 year-olds, 30% of 36-45 year-olds, and 19% of people 46 and over. Similarly, the algorithm does not recommend (fit below 40%) 25 people ages 18-25, 129 people ages 26-35, 73 people ages 36-45 and 45 people age 46 and over. That is 272 people total, 9% of whom are ages 18-25, 47% ages 26-35, 27% ages 36-45, and 16% age 46 and over.

In conclusion, the algorithm recommends and does not recommend profiles in very similar proportions as that of the sample distribution used in terms of age (8% ages 18-25, 42% ages 26-35, 32% ages 36-45, and 19% age 46 and over). Use of the algorithm can therefore be considered equitable and non-discriminatory in terms of age.

Also, the study of Cohen’s *d* statistic on the fit averages of each group ensures the equity and non-discrimination of algorithm use among the various groups. To manage this analysis 2 by 2, each group is compared to a second group that integrates all of the other age classes.

Average of the 18-25 year old group	Average of the other groups	Cohen’s *d* value	Effect size
51.00	51.75	-0.09	No effect

Average of the 26-35 year old group	Average of the other groups	Cohen's *d* value	Effect size
51.47	51.84	-0.04	No effect

Average of the 36-45 year old group	Average of the other groups	Cohen's *d* value	Effect size
51.84	51.63	0.02	No effect

Average of the 46 and over group	Average of the other groups	Cohen's *d* value	Effect size
52.00	51.63	0.04	No effect

The results presented in this second analysis validate the non-discrimination and equity of algorithm usage: the algorithm recommends profiles in almost identical proportions as the proportions at process input, according to gender and age.

Customer advisor

The mission of the customer advisor as defined for this project and by the C-ONE company, is as follows: "*provide a unique human and digital experience, create value for the group by developing customer uses.*"

The first step of the work consists in creating the predictive model. This model was built by a team of 3 expert psychologists, based on a translation of the C-ONE job description into the personality and motivation baseline of AssessFirst.

The dimensions integrated in the model are presented in the table below:

Questionnaire	Corresponding dimensions
SHAPE Personality	Seeks to persuade others
	Demonstrates diplomacy
	Is open to other people's ideas
	Accepts criticism
	Focuses on operational aspects
	Focuses on the positive
	Controls own feelings

DRIVE Motivations	Meet new people
	Worry about quality
	Having autonomy
	Working as part of a team
	Having a positive impact on the world
	Helping others
	Having a positive impact on the world

First analysis.

A first analysis of model equity was carried out, taking into consideration a general population. The distribution in terms of gender, age and disability are shown in the tables below.

Gender sample	Total	Men	Women
Global	374,841	188,351 (50%)	186,490 (50%)

Note: to ensure fair use, the algorithm should therefore recommend men and women in approximately 50/50 proportions (profile fit greater than or equal to 60%). The reasoning is the same for profiles that are not recommended (fit below 40%).

Age sample	Total	Age category	Distribution
Global	23,584	18-25	6461 (27%)
		26-35	8492 (36%)
		36-45	5026 (21%)
		46 and over	3605 (15%)

Note: to ensure fair use, the algorithm should therefore recommend people according to a very similar distribution by age. About 27% of 18-25 year-olds, 36% of 26-35 year-olds, 21% of 36-45 year-olds, and 15% of people 46 and over.

Disability sample	Total	With disability	Without disability
Global	27,958	2229 (8%)	25 -,729 (92%)

Note: to ensure fair use, the algorithm should therefore recommend people with disability and people without disability on approximately 8/92 proportions (profile fit greater than or equal to 60%). The reasoning is the same for profiles that are not recommended (fit below 40%).

Results of the gender analysis:

Fit	Men	Women
0 to 39%	47,976 (25%)	38,869 (21%)
40 to 49%	41,438 (22%)	39,849 (22%)

50 to 59%	60,595 (32%)	64,004 (34%)
60 to 100%	38,342 (20%)	43,768 (23%)

The algorithm recommends (fit above 60%) 38,342 men and 43,768 women - i.e. 82,110 people total, 47% of whom are men and 53% of whom are women. Similarly, the algorithm does not recommend (fit below 40%) 47,876 men and 38,869 women - i.e. 86,845 people total, 55% of whom are men and 45% of whom are women.

In conclusion, the algorithm recommends - and does not recommend - profiles of men and women in very similar proportions to the distribution of the sample used (50% men and 50% women). Use of the algorithm can therefore be considered equitable and non-discriminatory in terms of gender.

Also, the study of Cohen's *d* statistic on the fit averages of men and women ensures the equity and non-discrimination of algorithm use between the two groups:

Average of men	Average of women	Cohen's *d* value	Effect size
49.02	50.47	0.12	No effect

Results of the age analysis:

Fit	18-25	26-35	36-45	46 and over
0 to 39%	1375 (21%)	2149 (25%)	1208 (24%)	711 (20%)
40 to 49%	1415 (22%)	1873 (22%)	1102 (22%)	688 (19%)
50 to 59%	2190 (34%)	2733 (32%)	1635 (33%)	1268 (35%)
60 to 100%	1481 (23%)	1737 (20%)	1081 (22%)	938 (26%)

The algorithm recommends (fit above 60%) 1481 people ages 18-25, 1737 people ages 26-35, 1081 people ages 36-45, and 938 people age 46 and over. That is 5237 people total, 28% of whom are ages 18-25, 33% ages 26-35, 21% ages 36-45, and 18% age 46 and over. The algorithm does not recommend (fit below 40%) 1375 people ages 18-25, 2149 people ages 26-35, 1208 people ages 36-45, and 711 people age 46 and over. That is 5443 people total, 25% of whom are ages 18-25, 39% ages 26-35, 22% ages 36-45, and 13% age 46 and over.

In conclusion, the algorithm recommends and does not recommend profiles in very similar proportions as that of the sample distribution used in terms of age (27% ages 18-25, 36% ages 26-35, 21% ages 36-45, and 15% age 46 and over). Use of the algorithm can therefore be considered equitable and non-discriminatory in terms of age.

Also, the study of Cohen's *d* statistic on the fit averages of each group ensures the equity and non-discrimination of algorithm use among the various groups. To manage this analysis 2 by 2, each group is compared to a second group that integrates all of the other age classes.

Average of the 18-25 year old group	Average of the other groups	Cohen's *d* value	Effect size
50.21	49.67	0.04	No effect

Average of the 26-35 year old group	Average of the other groups	Cohen's *d* value	Effect size
49.05	50.25	-0.10	No effect

Average of the 36-45 year old group	Average of the other groups	Cohen's *d* value	Effect size
49.48	49.91	-0.03	No effect

Average of the 46 and over groupe	Average of the other groups	Cohen's *d* value	Effect size
51.28	49.56	0.15	No effect

Results of the disability analysis:

Fit	With disability	Without disability
0 to 39%	494 (22%)	5804 (23%)
40 to 49%	426 (19%)	5568 (22%)
50 to 59%	741 (33%)	8650 (33%)
60 to 100%	568 (25%)	5707 (22%)

The algorithm recommends (fit above 60%) 568 persons with a disability and 5707 persons without a disability - i.e. 6275 people total, 9% of whom are people with a disability and 91% of whom are people without a disability. Similarly, the algorithm does not recommend (fit below 40%) 494 persons with a disability and 5804 persons without a disability - i.e. 6298 people total, 8% of whom are people with a disability and 92% of whom are people without a disability.

In conclusion, the algorithm recommends - and does not recommend - profiles of people with a disability and people without a disability in very similar proportions to the distribution of the sample used (8% of people with a disability and 92% of people without a disability). Use of the algorithm can therefore be considered equitable and non-discriminatory in terms of disability.

Also, the study of Cohen's *d* statistic on the fit averages of people with a disability and people without a disability ensures the equity and non-discrimination of algorithm use between the two groups:

Mean with a disability	Mean without a disability	Cohen's *d* value	Effect size
50.64	49.95	0.05	No effect

The results presented in this first analysis validate the non-discrimination and equity in use of the algorithm: the algorithm recommends profiles in almost identical proportions as the proportions at process input, according to gender and age.

Second analysis.

A second analysis of model equity was carried out, taking into consideration a specific population of customer advisors. The distribution in terms of gender and age are shown in the tables below. *Note: Disability-related studies cannot be conducted with a specific sample due to the low number of people who register on the application indicating that they are project managers and have a disability.*

Gender sample	Total	Men	Women
Specific	16,877	7055 (42%)	9822 (58%)

Note: to ensure fair use, the algorithm should therefore recommend men and women in approximately 42/58 proportions (profile fit greater than or equal to 60%). The reasoning is the same for profiles that are not recommended (fit below 40%).

Age sample	Total	Age category	Distribution
Specific	3425	18-25	786 (23%)
		26-35	1542 (45%)
		36-45	784 (23%)
		46 and over	313 (9%)

Note: to ensure fair use, the algorithm should therefore recommend people according to a very similar distribution by age. About 23% of 18-25 year-olds, 45% of 26-35 year-olds, 23% of 36-45 year-olds, and 9% of people 46 and over.

Results of the gender analysis:

Fit	Men	Women
0 to 39%	1535 (22%)	1774 (18%)
40 to 49%	1483 (21%)	2059 (21%)
50 to 59%	2286 (32%)	3470 (35%)
60 to100%	1751 (25%)	2619 (27%)

The algorithm recommends (fit above 60%) 1751 men and 2619 women - i.e. 4370 people total, 40% of whom are men and 60% of whom are women. Similarly, the algorithm does not recommend (fit below 40%) 1535 men and 1774 women - i.e. 3309 people total, 46% of whom are men and 54% of whom are women.

In conclusion, the algorithm recommends - and does not recommend - profiles of men and women in very similar proportions to the distribution of the sample used (42% men and 58% women). Use of the algorithm can therefore be considered equitable and non-discriminatory in terms of gender.

Also, the study of Cohen's *d* statistic on the fit averages of men and women ensures the equity and non-discrimination of algorithm use between the two groups:

Average of men	Average of women	Cohen's *d* value	Effect size
50.53	51.35	0.072	No effect

Results of the age analysis:

Fit	18-25	26-35	36-45	46 and over
0 to 39%	162 (21%)	333 (22%)	167 (21%)	44 (14%)
40 to 49%	175 (22%)	326 (21%)	149 (19%)	58 (19%)
50 to 59%	263 (33%)	504 (33%)	270 (34%)	124 (40%)
60 to 100%	186 (24%)	379 (25%)	198 (25%)	87 (28%)

The algorithm recommends (fit above 60%) 186 people ages 18-25, 379 people ages 26-35, 198 people ages 36-45, and 87 people age 46 and over. That is 850 people total, 22% of whom are ages 18-25, 45% ages 26-35, 23% ages 36-45, and 10% age 46 and over. Similarly, the algorithm does not recommend (fit below 40%) 162 people ages 18-25, 333 people ages 26-35, 167 people ages 36-45 and 44 people age 46 and over. That is 706 people total, 19% of whom are ages 18-25, 40% ages 26-35, 20% ages 36-45, and 5% age 46 and over.

In conclusion, the algorithm recommends and does not recommend profiles in very similar proportions as that of the sample distribution used in terms of age (23% ages 18-25, 45% ages 26-35, 23% ages 36-45, and 9% age 46 and over). Use of the algorithm can therefore be considered equitable and non-discriminatory in terms of age.

Also, the study of Cohen's *d* statistic on the fit averages of each group ensures the equity and non-discrimination of algorithm use among the various groups. To manage this analysis 2 by 2, each group is compared to a second group that integrates all of the other age classes.

Average of the 18-25 year old group	**Average of the other groups**	**Cohen's *d* value**	**Effect size**
50.47	50.78	-0.02	No effect

Average of the 26-35 year old group	**Average of the other groups**	**Cohen's *d* value**	**Effect size**
50.37	50.97	-0.05	No effect

Average of the 36-45 year old group	**Average of the other groups**	**Cohen's *d* value**	**Effect size**
50.83	50.68	0.01	No effect

Average of the 46 and over group	**Average of the other groups**	**Cohen's *d* value**	**Effect size**
51.89	50.52	0.11	No effect

The results presented in this second analysis validate the non-discrimination and equity of algorithm usage: the algorithm recommends profiles in almost identical proportions as the proportions at process input, according to gender and age.

Qualified technician

The mission of the qualified technician, as defined for this project and by the C-ONE company, is as follows: "*Independently perform interventions in production and/or maintenance on the network or on customer premises and support customers in their use of the company's products and services.*"

The first step of the work consists in creating the predictive model. This model was built by a team of 3 expert psychologists, based on a translation of the C-ONE job description into the personality and motivation baseline of AssessFirst.

The dimensions integrated in the model are presented in the table below:

Questionnaire	Corresponding dimensions
SHAPE Personality	Does not seek to lead others
	Demonstrates diplomacy
	Is open to other people's ideas
	Accepts criticism
	Demonstrates inventiveness
	Adapts to change
	Organises work methodically
	Perseveres when confronted with obstacles
	Demonstrates responsiveness
DRIVE Motivations	Analyse data
	Meet new people
	Have clearly defined tasks
	Worry about quality
	Having autonomy
	Working in a disciplined environment
	Helping others

First analysis.

A first analysis of model equity was carried out, taking into consideration a general population. The distribution in terms of gender, age and disability are shown in the tables below.

Gender sample	Total	Men	Women
Global	374,841	188,351 (50%)	186,490 (50%)

Note: to ensure fair use, the algorithm should therefore recommend men and women in approximately 50/50 proportions (profile fit greater than or equal to 60%). The reasoning is the same for profiles that are not recommended (fit below 40%).

Age sample	Total	Age category	Distribution
Global	23,584	18-25	6461 (27%)
		26-35	8492 (36%)
		36-45	5026 (21%)
		46 and over	3605 (15%)

Note: to ensure fair use, the algorithm should therefore recommend people according to a very similar distribution by age. About 27% of 18-25 year-olds, 36% of 26-35 year-olds, 21% of 36-45 year-olds, and 15% of people 46 and over.

Disability sample	Total	With disability	Without disability
Global	27,958	2229 (8%)	25,729 (92%)

Note: to ensure fair use, the algorithm should therefore recommend people with disability and people without disability on approximately 8/92 proportions (profile fit greater than or equal to 60%). The reasoning is the same for profiles that are not recommended (fit below 40%).

Results of the gender analysis:

Fit	Men	Women
0 to 39%	20,800 (11%)	17,692 (9%)
40 to 49%	66,368 (35%)	61,559 (33%)
50 to 59%	77,908 (41%)	79,595 (43%)
60 to 100%	23,275 (12%)	27,644 (15%)

The algorithm recommends (fit above 60%) 23,275 men and 27,644 women - i.e. 50,919 people total, 46% of whom are men and 54% of whom are women. Similarly, the algorithm does not recommend (fit below 40%) 20,800 men and 17,682 women - i.e. 38,492 people total, 41% of whom are men and 59% of whom are women.

In conclusion, the algorithm recommends - and does not recommend - profiles of men and women in very similar proportions to the distribution of the sample used (50% men and 50% women). Use of the algorithm can therefore be considered equitable and non-discriminatory in terms of gender.

Also, the study of Cohen's *d* statistic on the fit averages of men and women ensures the equity and non-discrimination of algorithm use between the two groups:

Average of men	Average of women	Cohen's *d* value	Effect size
50.32	51.17	0.09	No effect

Results of the age analysis:

Fit	18-25	26-35	36-45	46 and over
0 to 39%	603 (9%)	841 (10%)	538 (11%)	277 (8%)
40 to 49%	2054 (32%)	2913 (34%)	1766 (35%)	1114 (31%)
50 to 59%	2842 (44%)	3584 (42%)	2051 (41%)	1620 (45%)
60 to 100%	962 (15%)	1154 (14%)	671 (13%)	594 (16%)

The algorithm recommends (fit above 60%) 962 people ages 18-25, 1154 people ages 26-35, 671 people ages 36-45, and 594 people age 46 and over. That is 3381 people total, 28% of whom are ages 18-25, 34% ages 26-35, 20% ages 36-45, and 17% age 46 and over. The algorithm does not recommend 603 people ages 18-25, 841 people ages 26-35, 538 people ages 36-45, and 277 people age 46 and over. That is 2259 people total, 27% of whom are ages 18-25, 37% ages 26-35, 24% ages 36-45, and 12% age 46 and over.

In conclusion, the algorithm recommends and does not recommend profiles in very similar proportions as that of the sample distribution used in terms of age (27% ages 18-25, 36% ages 26-35, 21% ages 36-45, and 15% age 46 and over). Use of the algorithm can therefore be considered equitable and non-discriminatory in terms of age.

Also, the study of Cohen's *d* statistic on the fit averages of each group ensures the equity and non-discrimination of algorithm use among the various groups. To manage this analysis 2 by 2, each group is compared to a second group that integrates all of the other age classes.

Average of the 18-25 year old group	Average of the other groups	Cohen's *d* value	Effect size
51.33	50.95	0.04	No effect

Average of the 26-35 year old group	Average of the other groups	Cohen's *d* value	Effect size
50.78	51.20	-0.14	No effect

Average of the 36-45 year old group	Average of the other groups	Cohen's *d* value	Effect size
50.55	51.19	-0.07	No effect

Average of the 46 and over group	Average of the other groups	Cohen's *d* value	Effect size
51.96	50.89	0.12	No effect

Results of the disability analysis:

Fit	With disability	Without disability
0 to 39%	180 (9%)	2609 (10%)
40 to 49%	702 (31%)	8653 (34%)
50 to 59%	984 (44%)	10,972 (43%)
60 to 100%	363 (16%)	3495 (14%)

The algorithm recommends (fit above 60%) 363 persons with a disability and 3495 persons without a disability - i.e. 3858 people total, 9% of whom are people with a disability and 91% of whom are people without a disability. Similarly, the algorithm does not recommend (fit below 40%) 180 persons with a disability and 2609 persons without a disability - i.e. 2789 people total, 6% of whom are people with a disability and 94% of whom are people without a disability.

In conclusion, the algorithm recommends - and does not recommend - profiles of people with a disability and people without a disability in very similar proportions to the distribution of the sample used (8% of people with a disability and 92% of people without a disability). Use of the algorithm can therefore be considered equitable and non-discriminatory in terms of disability.

Also, the study of Cohen's *d* statistic on the fit averages of people with a disability and people without a disability ensures the equity and non-discrimination of algorithm use between the two groups:

Mean with a disability	Mean without a disability	Cohen's *d* value	Effect size
51.79	50.83	0.11	No effect

The results presented in this preliminary analysis validate the non-discrimination and equity in use of the algorithm: the algorithm recommends profiles in almost identical proportions as the proportions at process input, according to gender and age.

Second analysis.

A second analysis of model equity was carried out, taking into consideration a specific population of customer advisors. The distribution in terms of gender and age are shown in the tables below. *Note: Disability-related studies cannot be conducted with a specific sample due to the low number of people who register on the application indicating that they are project managers and have a disability.*

Gender sample	Total	Men	Women
Specific	2630	2439 (93%)	191 (7%)

Note: to ensure fair use, the algorithm should therefore recommend men and women in approximately 93/7 proportions (profile fit greater than or equal to 60%). The reasoning is the same for profiles that are not recommended.

Age sample	Total	Age category	Distribution
Specific	521	18-25	60 (12%)
		26-35	139 (27%)
		36-45	175 (34%)
		46 and over	147 (28%)

Note: to ensure fair use, the algorithm should therefore recommend people according to a very similar distribution by age. About 12% of 18-25 year-olds, 27% of 26-35 year-olds, 34% of 36-45 year-olds, and 28% of people 46 and over.

Results of the gender analysis:

Fit	Men	Women
0 to 39%	188 (8%)	12 (7%)
40 to 49%	751 (31%)	63 (33%)
50 to 59%	1089 (45%)	88 (46%)
60 to 100%	411 (17%)	28 (15%)

The algorithm recommends (fit above 60%) 411 men and 28 women - i.e. 439 people total, 94% of whom are men and 6% of whom are women. Similarly, the algorithm does not recommend (fit below 40%) 188 men and 12 women - i.e. 200 people total, 94% of whom are men and 6% of whom are women.

In conclusion, the algorithm recommends - and does not recommend - profiles of men and women in very similar proportions to the distribution of the sample used (93% men and 7% women). Use of the algorithm can therefore be considered equitable and non-discriminatory in terms of gender.

Also, the study of Cohen's *d* statistic on the fit averages of men and women ensures the equity and non-discrimination of algorithm use between the two groups:

Average of men	Average of women	Cohen's *d* value	Effect size
52.02	51.52	-0.05	No effect

Results of the age analysis:

Fit	18-25	26-35	36-45	46 and over
0 to 39%	4 (7%)	7 (5%)	20 (11%)	13 (9%)
40 to 49%	19 (32%)	57 (41%)	56 (32%)	43 (29%)
50 to 59%	26 (43%)	53 (38%)	83 (47%)	68 (46%)
60 to 100%	11 (18%)	22 (16%)	16 (9%)	23 (16%)

The algorithm recommends (fit above 60%) 11 people ages 18-25, 22 people ages 26-35, 16 people ages 36-45, and 23 people age 46 and over. That is 72 people total, 15% of whom are ages 18-25, 31% ages 26-35, 22% ages 36-45, and 32% age 46 and over. The algorithm does not recommend (fit below 40%) 4 people ages 18-25, 7 people ages 26-35, 20 people ages 36-45, and 13 people age 46 and over. That is 44 people total, 9% of whom are ages 18-25, 16% ages 26-35, 45% ages 36-45, and 30% age 46 and over.

In conclusion, the algorithm recommends and does not recommend profiles in proportions close to those of the sample distribution used in terms of age (12% ages 18-25, 27% ages 26-35, 34% ages 36-45, and 28% age 46 and over). Though slight deviations appear, they are to be considered while keeping in mind the relatively small sample size.

Also, the study of Cohen's *d* statistic on the fit averages of each group ensures the equity and non-discrimination of algorithm use among the various groups. To manage this analysis 2 by 2, each group is compared to a second group that integrates all of the other age classes.

Average of the 18-25 year old group	Average of the other groups	Cohen's *d* value	Effect size
51.95	51.32	0.07	No effect

Average of the 26-35 year old group	Average of the other groups	Cohen's *d* value	Effect size
51.08	51.49	-0.04	No effect

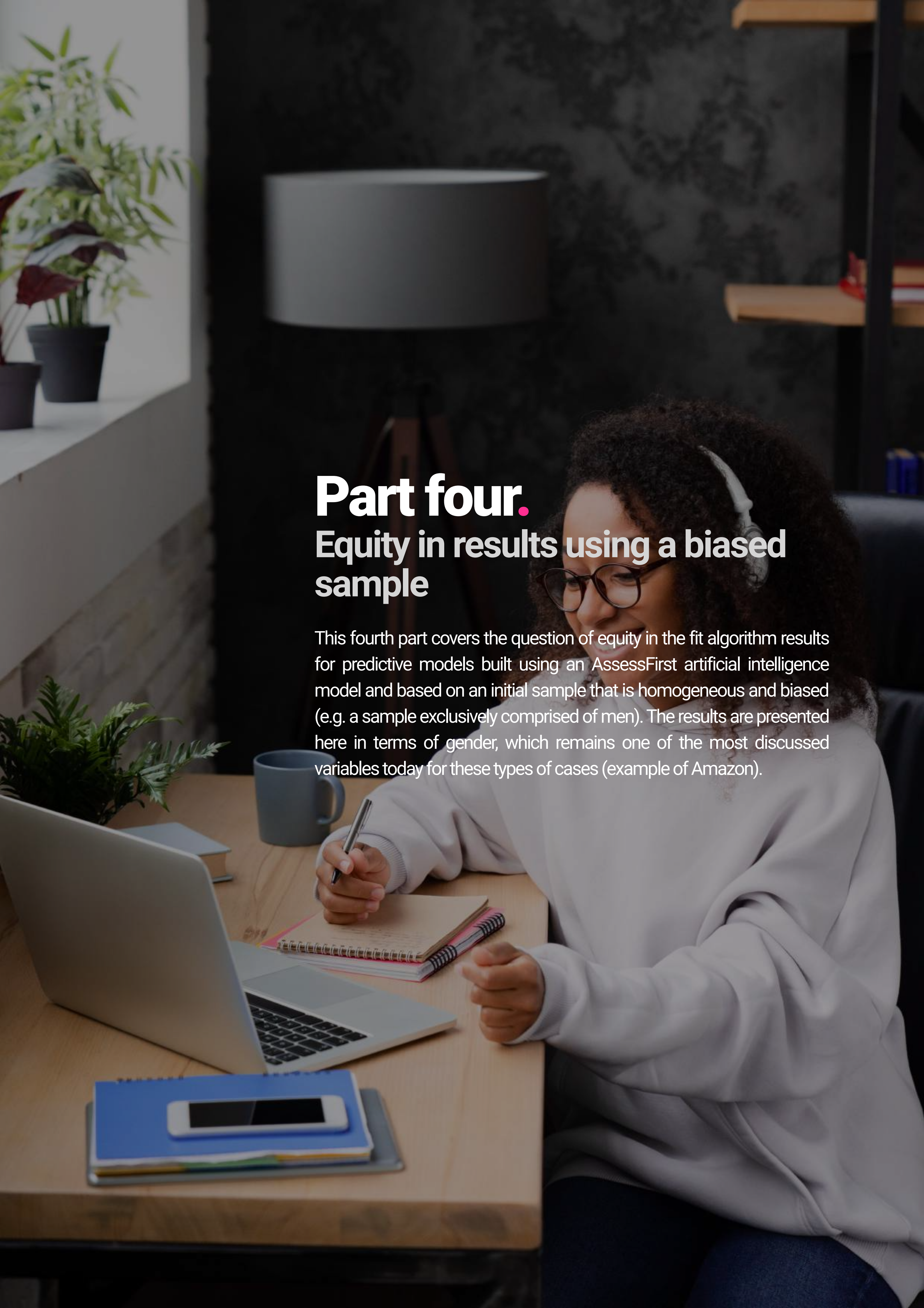
Average of the 36-45 year old group	Average of the other groups	Cohen's *d* value	Effect size
50.53	51.77	-0.15	No effect

Average of the 46 and over group	Average of the other groups	Cohen's *d* value	Effect size
51.60	51.32	0.03	No effect

The results presented in this second analysis validate the non-discrimination and equity of algorithm usage: the algorithm recommends profiles in almost identical proportions as the proportions at process input, according to gender and age.

Section conclusion.

Use of algorithms in HR processes and decisions raise the question of equity. The examples presented in this section therefore allow us to demonstrate, with the analysis of various predictive models, that the use of algorithms proposed by AssessFirst are indeed non-discriminatory and equitable. The characteristics (distribution) of people who are recommended or not recommended by the algorithm (process output) are similar to those at process input when it comes to gender and age. In other words, for a specific position, the profiles that will be recommended by the algorithm to the hiring manager present demographic characteristics that are similar to those of the entire pool of candidates applying to the position.



Part four.

Equity in results using a biased sample

This fourth part covers the question of equity in the fit algorithm results for predictive models built using an AssessFirst artificial intelligence model and based on an initial sample that is homogeneous and biased (e.g. a sample exclusively comprised of men). The results are presented here in terms of gender, which remains one of the most discussed variables today for these types of cases (example of Amazon).

EQUITY IN THE RESULTS USING A BIASED SAMPLE.

Three years ago, Amazon carried out an experiment in order to automate pre-selection of CVs. The general idea was to develop an algorithm to which you could feed 100 CVs and it would rate each one on a scale of 5 stars so that the algorithm would always pre-select the 5 candidates with the highest probabilities of success at Amazon. Result: the recommendations made had a tendency to exclude the CVs of women, almost systematically. This algorithm, built on the basis of mostly male hires at Amazon over past ten years, therefore created an algorithmic gender bias. For more details, see this article.

However, concluding from this experiment that algorithms are dangerous or "sexist" would be a terrible mistake. In Amazon's case, even though the nature of the base sample was biased (Amazon, at least at the time, was a company where over 60% of employees were men), what really led to the algorithm's gender bias was the data used to predict future performance (taken from the CV) rather than the fact that the sample used to train the algorithm was mostly made up of men.

The study below therefore aims to demonstrate this argument by:

- Building a predictive model based on the analysis of a training sample comprised 100% of men;
- Using only data that is naturally not very biased in terms of gender distribution - data relating to personality and motivation;
- Showing that, despite the conditions of model creation, our algorithm will recommend - and not recommend - men and women in almost identical proportions (about 50/50) when using a neutral sample.

Construction of the predictive model.

For this study, a predictive model was created based on the analysis of profiles from a sample of **169,864 people, 100% of whom were men and 0% women**, the average age was 35 years old, and most had a bachelor's (36.48%) or master's degree (33.53%).

The statistical analysis of the specific characteristics of this sample in terms of personality and motivation allowed us to isolate several elements that were slightly more prominent, and therefore to create a predictive model including the following dimensions:

Questionnaire	Corresponding dimension
SHAPE Personality	Does not try to influence
	Prefers to be approached
	Speaks in a forthright manner
	May react to criticism
	Manages to focus his/her attention
	Is interested in abstract ideas
	Demonstrates inventiveness
	Perseveres when confronted with obstacles
	Focuses on the positive
DRIVE Motivations	Analyse data
	Having a global objective
	Having a positive impact on the world
	Remuneration is not their priority
	Avoids constant competition
	Helping others

Equity of the model created.

The equity of the model was analyzed by taking into consideration a general population. The distribution in terms of gender is shown in the table below:

Gender sample	Total	Men	Women
Global	332,587	169,864 (51%)	162,723 (49%)

Note: to ensure fair use, the algorithm should therefore recommend men and women in approximately 51/49 proportions (profile fit greater than or equal to 60%). The reasoning is the same for profiles that are not recommended (fit below 40%).

Results of the gender analysis:

Fit	Men	Women
0 to 39%	21,358 (13%)	21,508 (13%)

40 to 49%	31,653 (19%)	32,761 (20%)
50 to 59%	50,016 (29%)	50,545 (31%)
60 to 100%	66,837 (39%)	57,909 (36%)

The algorithm recommends (fit above 60%) 66,837 men and 57,909 women - i.e. 124,746 people total, 53% of whom are men and 47% of whom are women. Similarly, the algorithm does not recommend (fit below 40%) 21,358 men and 21,508 women - i.e. 42,866 people total, 50% of whom are men and 50% of whom are women.

In conclusion, the algorithm recommends - and does not recommend, profiles of men and women in very similar proportions to the distribution of the sample used (51% men and 49% women). Use of the algorithm can therefore be considered equitable and non-discriminatory in terms of gender.

Also, the study of Cohen's *d* statistic on the fit averages of men and women ensures the equity and non-discrimination of algorithm use between the two groups:

Average of men	Average of women	Cohen's *d* value	Effect size
56	55	0.07	No effect

Section conclusion.

The example presented in this section demonstrates that, even when building a predictive model based on the analysis of a biased sample (e.g. over-representation of men in the training sample), it is the type of data that impacts results most. In our example, even though the model was created by taking only men into consideration, the algorithm then goes on to recommend men and women in almost equal proportions - the results are therefore blind to the demographic characteristics of the original sample. It turns out that considering algorithms exclusively as a threat or as dehumanizing to HR processes is in fact an attribution error. This limits our ability to understand algorithms as a solution for solving discrimination issues in companies. Recruiting talent using algorithms based on personality and motivation data therefore ensures a natural re-balancing of genders in the workplace.

GENERAL CONCLUSION.

At AssessFirst, we believe that in order to sustainably change things on a deep level, it is imperative that the solution we provide serve the interests of both job applicants and of companies. Without this fundamental balance, we do not think that any significant or lasting change is possible. We therefore designed a solution that allows individuals and companies to better understand themselves and truly make the best decisions in a very concrete way. So far, more than 3500 companies across 40 countries and more than 5,000,000 people have used AssessFirst successfully and therefore participated in the creation of a more efficient and equitable world.

The reliability and fairness of AssessFirst analyses and algorithms are indeed recognized. Our teams do everything possible to ensure the fairness of predictive analyses and to guarantee that the use of our algorithms in decision-making processes do not lead to discrimination via algorithmic biases. And that is what the study presented here demonstrates: fairness in the results obtained from questionnaire responses (in terms of gender, age, ethnic origin and disability), and fairness in the results and recommendations produced by the algorithm. Our solution makes it possible to considerably develop diversity in companies, as shown by our client Spencer Ogen, who improved his diversity by 22% by using AssessFirst's AI.

AssessFirst also highly stresses the accessibility of the solution for all populations. Across various levels of action, we ensure that each individual can access the solution and have a high-quality experience, regardless of their academic or professional experience, their age, disability or gender.

About AssessFirst

AssessFirst developed a predictive recruiting solution to allow companies to predict how well candidates and teammates would succeed and prosper in their work. The AssessFirst solution analyzes data of more than 5,000,000 profiles, including job applicants, employees and hiring professionals. Today, more than 3500 companies use AssessFirst to increase their performance by up to 25%, lowering hiring costs by 20% and reducing turnover of their employees by 50%.

To learn more: www.assessfirst.com