Vocabulary diversity in Dutch hip-hop lyrics, in relation to artist gender, age and popularity

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Abstract

This research aims to contribute to the understanding of why it is harder for Dutch female hip-hop artists to be part of the hip-hop scene in the Netherlands. The hip-hop industry can be seen as quite a misogynistic industry due to its lyrics and visuals. Therefore, often gives the impression that the Dutch hip-hop scene is a world dominated by men and that this music scene is more difficult or simply less attractive for a woman to enter. While it is outside of the scope of this research to investigate every aspect of how Dutch male and female hip-hop artists differ, this research investigates the lexical diversity in Dutch hip-hop lyrics, in relation to artist gender, age and popularity. Findings from this research suggest that there is a significant difference in the lexical diversity of male artists and female artists. But artists' lexical diversity is not affected by the age of the artist. Additionally, it was observed that artists' popularity is not influenced by their lexical diversity.

1. Introduction

Hip-hop originated in the 1970s in a de-industrialized urban environment, better known as the South Bronx neighbourhood of New York (Keyes, 2004). Here African American and Caribbean communities attempted to deal with feelings of marginalization, the lack of economic- and social opportunity and oppression (Rose, 1994). This cultural and musical movement provided the listeners with an identity. The movement continued to grow due to technological advances. In the mid-seventies, new music techniques arose, such as mixing records and new sound systems - allowing the movement to set itself apart in terms of style. Furthermore, due to MTV's widespread popularity in the early '80s, a TV channel centred on the latest music trends, the movement became mainstream. This brought hip-hop to become quite literally 'hip' and aided in the commercialization of this emerging music trend (Rose, 2008). Because of the popularity of this hip-hop scene, the number of rap and hip-hop artists grew (Markus, van der Hoeven, & Verboord, 2012).

In America, the gangsta-rap sub-genre grew out of hip-hop. Textual features of gangsta-rap include references to drug dealing and the difficult life on the street. Rose (2008) describes this gangsta-rap as the black-gangsta-pimp-ho-rap. Rap that gives a stereotypical image of black gangstas and whores, often containing misogynistic expressions (Rose, 2008). This rap became increasingly commercial in the '90s through rappers like Snoop Dogg and Dr. Dré. It is striking that this rap with misogyny became so popular, mainly because the emancipation of black culture was an important inspiration when hip-hop was in its infancy (Rose, 2008).

The explanation for the popularization of gangsta-rap is the influence that demand has on the music industry. Music that glorifies violence and sexual dominance sells well, so therefore, the industry dictates that these become guiding themes (Monk-Turner & Sylvertooth, 2008; Rose, 2008). This creates a vicious cycle. Initially, an artist might use depictions of violence and sexual dominance to gain recognition, status or as an indication of their masculinity. The artist, knowing how lucrative this type of music is, might not even be singing about lived-experiences or believe in the messaging they put out (Adams & Fuller, 2006). Once they have gained a foothold in the industry, they can continue making money from this lucrative ideology. Hence, while these depictions of violence arose out of a movement of emancipation for black African and Caribbean Americans, due to its popularization has become appropriated instead for financial gains.

The hip-hop music genre also became popular in the Netherlands in the late 1970's. Young people with roots in former colonies such as Suriname and the Dutch Antilles started rapping in their neighbourhoods such as the Amsterdam Bijlmer. People in these neighbourhoods started to identify themselves with their cultural peers across the Atlantic Ocean and started to imitate American rap. This marks the start of the Dutch hip-hop (Markus, van der Hoeven, & Verboord, 2012). Nowadays, the Dutch hip-hop scene is unprecedentedly larger than before. Artists such as Bizzey, Ronnie Flex, Famke Louise and Lil' Kleine have become an integral part of Dutch TV, music charts and festivals, which makes it no surprise that since 2018 it is the most popular music genre in the Netherlands (Steenhoff, 2021; NOS, 2018).

When looking at Dutch hip-hop playlists on Spotify or iTunes, few to no women are represented in these lists. However, the women that are present in these lists are not as frequently listened to as their male counterparts. In 2018 the top five most played artists (regardless of genre or nationality) in the Netherlands are all Dutch male hip-hop artists. In 2021 this same top five consisted of four Dutch male hip-hop artists. This can give the impression that the Dutch hip-hop scene is a world dominated by men and that this music scene is more difficult or simply less attractive for a woman to enter into (de Roest, 2017).

Another thing that makes it harder for women is the dichotomy of their presence in the media. When female artists are talked about it is with much more scrutiny compared to their male counterparts (de Roest, 2017). A quick glance at comment sections underneath music videos posted by female artist to YouTube reveals this. Comments such as 'Ze is vergeten dat ze een vrouw is' ('She forgot that she is a woman') or 'Ze is best wel hard voor een vrouw'. ('She is quite dope, for a woman'), are not uncommon. (NPO3, 2017, 3voor12, 2020). Furthermore, on the rare occasion that media outlets decide to write articles about female artists it is often in the light drama, controversy or their difficult fight to the top. Male artists are viewed in a more positive light and often get more in-depth coverage on media.

Furthermore, the hip-hop industry can be seen as quite a misogynistic industry due to its lyrics and visuals. The lyrics often describe women in a degrading manner and include a lot of sexual objectifications, that can even turn quite violent. One of the most popular artists, Bizzey, often portrays women as sexual object in his music, with lyrics such as: 'Trek je jurkje maar naar boven en doe de rest naar beneden.' ('Pull up your dress, and pull the rest down'). 'Gooi je face omlaag, gooi je bil omhoog.' ('Put your face down, and throw your ass up'). 'Van buiten ben je engel, maar van binnen ben je slet' ('On the outside you're an angel, but on the inside you're a slut'). This kind of lyrics influences the listener into thinking it is okay to talk about women in this way and for women to accept this type of violence against them (Johnson, 1995). Furthermore, when men listen to misogynistic (rap) music, it can arouse sexually aggressive behaviour (Barongan, 1995, Cobb & Boettcher, 2007).

The music videos accompanying these types of songs provide an additional layer of influence. So are women who watch aggressive video clips are more likely to accept violence towards women afterwards (Johnson, 1995). Sexual objectification is prevalent in the lyrics and in the music videos, often featuring scantily clad women (Adams & Fuller, 2006). Dutch artist Riza Tisserand says this puts female artists in a difficult position, since they must adhere to these standards. He states that Dutch female rappers have the choice of being either over-sexualized like American artists such as Nicki Minaj or be hyper masculine, at the risk of losing their male audience (NOS, 2016). Due to these sexist music lyrics and videos, female artists can be more prone to the conscious or unconscious idea that they must engage in these sexist standards, making them less able to focus on their artistic (De Roest, 2017). This displays a gender issue in the hip-hop scene. Ideas of women being objectified or exploited or otherwise degraded, which continue to circulate in rap music, make it difficult for female performers to be taken seriously (De Roest, 2017).

Taking the above into account, it begs the question whether it is warranted that female artists seem to struggle in this industry. While it is outside of scope of this research to investigate every aspect of how Dutch male and female hip-hop artists differ, this research aims to see how they differ in their lexical use. In so doing, this research aims to contribute to the understanding of why it is harder for female artists to be part of the hip-hop scene or whether they deserve more credit. Furthermore, this research investigates if there is an influence by artist' age on their lexical diversity of their songs and to see if there is a connection between the popularity of the artist and their lexical diversity. This study thus adds value to the fields of linguistics and music culture.

Since little prior research exists about Dutch hip-hop, first an outline of how hip-hop came to the Netherlands will be explained, to get a better understanding of this music scene, followed by a framework of relevant concepts. Next, the hypotheses will be stated followed by the method. Lastly, the results are presented and discussed with pointers to future research.

2. Theoretical background

2.1 Brief history of Dutch hip-hop

In the 1980's hip-hop became a trend in the Netherlands, with Osdorp Posse and Extince as best-known early representatives. The way Osdorp Posse attracted attention was by literally translating American rap lyrics and terms to Dutch (Markus, van der Hoeven, & Verboord, 2012). In 1987 Extince released his first single, as did Rudeboy, who became the first black Dutch hip-hop artist (Wermuth, 2001). Two years later Djax Records was founded, by Saskia Slegers, this was the first label that released hip-hop records in the Netherlands, representing artists including Osdorp Posse. Other hip-hop labels and artists followed, but did not persuade a large audience, resulting in their music becoming more of an underground movement. Nevertheless, hip-hop music mixed with dance music ended up in the charts, due to the radio and television which broadcasted this type of mixed hip-hop (Markus, van der Hoeven, &

Verboord, 2012). Around the turn of the century, hip-hop had infiltrated the Dutch mainstream culture and became part of other cultural segments such as theatre and literature. At this time Dutch hip-hop (or Nederhop) also became popular with the album-buying public (Wermuth, 2001).

In the beginning of the 21st century a new generation (mostly of Moroccan-Dutch descent) rappers emerged in the Netherlands, such as Ali B who became one of the most successful Dutch rappers. Other successful rappers and rap formations followed such as Brainpower, Opgezwolle, Kempi, Fresku and De Jeugd van Tegenwoordig. The latter named formation entered the hip-hop music scene in 2005 with their big hit 'Watskebeurt?', in which slang is mixed with a self-invented language. This rap formation, which was first seen as a one-hit wonder, grew into one of the most successful Nederhop formations (Markus, van der Hoeven, & Verboord, 2012).

Due to the internet era with its upcoming distribution channels such as YouTube and Spotify, hip-hop is growing into a popular youth culture. In 2013, when the number of unique streams became the indication for the music charts, Nederhop developed into one of the most popular music genres in the Netherlands. In 2015, various artists from the Dutch record label Top Notch made the album New Wave, which is only available online, and became very successful due to the hit 'Drank & Drugs' by Ronnie Flex and Lil Kleine. That year these artists won the award 'Popprijs' (an award for the artist(s) with the most important contribution to Dutch pop music in the past year), which is seen in the Dutch music scene and the media as a sign that the internet generation in hip-hop has now really established itself (De Roest, 2020).

2.2 Misogyny in hiphop and rap

While hip-hop has thus become a very popular genre, it is simultaneously well known for its provocative and misogynistic lyrics. Monk-Turner and Sylvertooth (2008) cite the music industry's power as one of the main drivers of provocative lyrics. In their research they analysed offensive words in hip-hop and rap lyrics, with a corpus of 180 arbitrary songs from 18 random artists. Through content analysis they compiled a list of the six most common words in hip-hop and rap lyrics (bitch, ho, dick, nigga, fuck and shit), and studied how often these words were used by male and female artists. The conclusion of their study was that there is a significant difference in the use of these six common words, with women using far less of these words. They found a significant sex difference when using the word 'ho'. A third of male rappers versus a fifth of female rappers used 'ho' at least once in their lyrics. The explanation for using insulting word towards women, can be found in the power of the music industry that encourages the use of this degradation, since it sells well (Monk-Turner, Sylvertooth, 2008).

The studies focusing on the driver behind these types of lyrics indicate that the music industry is the cause of misogynistic lyrics (Monk-Turner & Sylvertooth, 2008, and Rose, 2008) . But it is not only the music industry that keeps this type of music an ongoing trend. Because the same can be said about the public. As long as the public continues to listen to music with misogynistic lyrics, the music industry will not require its artists to change their language

(Weitzer & Kurbin, 2009). Hence it can be said that it simply comes down to supply and demand.

2.3 Vocabulary in hip-hop

A part of the quality of hip-hop is determined by the linguistic component. Artists want to voice their musical expression in a proper way. They can for example use their ethnic backgrounds with different linguistic elements (such as borrowing) to achieve a more diverse result in their self-expression through lyrics. Factors such as this (consciously or unconsciously) contribute to whether an artist is considered good or not (De Roest, 2017).

In 2014 Matt Daniels decided to rank hip-hop artists by the number of unique words used in their lyrics, to see if their vocabulary was as good as Shakespeare's and Melville. An intriguing juxtaposition since Shakespeare and Melville's are typically seen as highly regarded literary figures whereas hip-hop has a negative connotation in society, particularly linguistically speaking. To compare the lexical diversity of rappers to Shakespeare, he took the first 35000 words from lyrics of the 85 most famous hip-hop artists in America. For Shakespeare, the first 5000 words of the works: Hamlet, Romeo and Juliet, Othello, Macbeth, As You Like It, Winter's Tale, and Troilus and Cressida were used. For Melville, he used the first 35000 words in Moby Dick (Daniels, 2014). Daniels calculated the Type-token ratio (The TTR is a number that depicts the ratio between the total number of words as tokens, and the number of unique words in a text as types), for each artist using token analysis. In this method, each unique word is counted as one (Templin, 1957). This includes words that vary in spelling but are semantically the same. Daniels gives the example; 'pimps, pimp, pimping, and pimpin' and states that those words are counted as four unique words (Daniels, 2014). Furthermore, the apostrophes are removed from the dataset to avoid issues with getting more unique words. (Templin, 1957).

Hip-hop artists commonly use a lot of slang in their lyrics which does have an influence on the number of tokens, thus an impact on the TTR. The rapper with the most unique vocabulary was Aesop Rock with 7392 unique words. Which is (1370 words) more than Melville and Shakespeare (2222 words) and shows that artists indeed have similar lexical diversity when compared to praised literary figures (Daniels, 2014).

In 2017 researchers Reuneker, Waszink & Van der Wouden decided to apply Daniels's (2014) ranking to Dutch hip-hop artists and compared them to the well-known Dutch author Harry Mulisch. This study was not fully comparable in results compared to the American study. Few Dutch hip-hop artists were able to reach the lexical diversity of Harry Mulisch. A major difference in the Dutch study is that they stated that there are no (Dutch) female hip-hop artists in the ranking. They stated that this is because of the lack of female artists in the Dutch hip-hop scene, thus the researchers could not find enough lyrics of females to get them in the ranking (Reuneker, Waszink & Van der Wouden, 2017). Nowadays there are way more female artists in the Dutch hip-hop scene, and we can start to investigate this now.

2.4 Gender and language

Differences in gender and their use of language is a widely researched topic. Lakoff (1973) pioneered the field of gendered language with his study on the prevalence of hedging and tag questions in women's use of language when compared to men. Further studies have found men to use more direct language when formulating questions using for example 'let's go get food' instead of 'Does anyone want to get some food?' (Mulac et al, 1988). Research also indicates that women use more uncertainty when speaking, for example using phrases such as 'I wonder if…' (Hartman, 1976; Mulac & Lundell, 1994; Poole, 1979).

This study focuses on gender differences in lexical diversity in men and women. In linguistics, the study of lexicality is defined as "of or relating to words or the vocabulary of a language as distinguished from its grammar and construction". Women use more intense adverbs and use more words to place question marks over a statement. (Biber, Conrad, & Reppen, 1998; Mulac, Bradac, & Gibbons 2001; Newman et al, 2008). Men use more curse words, longer words and use more references to objects and locations or places. (Newman et al, 2008).

So, while there are differences in language use between the genders. There are almost no studies conducted on more specific social groups, specific backgrounds, or cultural divisions. For example, when it comes to gender differences in minority languages such as African American English or in the use of Slang – frequently used in English rap lyrics – the research field is very small.

2.5 Age and vocabulary

Differences in vocabulary can be found regarding gender, but also regarding age. This is a widely researched topic, especially when studied among different age groups. Researchers Sullivan and Brown (2015) studied the change in vocabulary scores between the ages of 16 and 42 and the effect of social background, education and reading behaviour in childhood and adulthood. They retrieved the data from the 1970 British Cohort study (Sullivan & Brown, 2015). Which is a study that follows 17000 people born the week of 5 – 11 April 1970 in the United Kingdom, by collecting data through surveys (Elliott & Shepherd, 2006). The research of Sullivan and Brown (2015) analyzed data from 4523 male and 4909 female participants. The study shows that the respondents have a strong improvement in their vocabulary scores between the age of 16 and 42 (mean improvement of 8%). For the group of age 16 men had lower scores in their vocabulary compared to women. However, when reaching the age of 42 men scored higher with a mean of 64% compared to 62%. Thus, men made more progress in their vocabulary compared to women. In addition, the study finds that progress in vocabulary is found between adolescence and mid-life. This improvement varies based on reading habits and activities in both childhood and adulthood.

Lastly, Verhaeghen (2003) also concludes that vocabulary scores measured in younger and older adults are age sensitive. The study did a meta-analysis on ageing and vocabulary scores, examining a total of 210 articles containing 324 independent pairings of younger adults (average age older than 18 and younger than 30) and older adults (average age of 60 and older). The results showed that younger adults scored lower on vocabulary tests than older adults thus, age has a positive effect on vocabulary scores. Adults scoring 0.80 SD (standard deviation) higher than younger adults. However, the study gives an explanation of the older adults having more educational experience which could have a positive bias on the outcome of their higher vocabulary scores than the younger adults. Furthermore, the study states that not only does having longer educational experience have an influence, but also years of completed education have an impact instead of the final reach of years of education of the participants.

2.6 Lexical diversity and its measurements

Lexical diversity (LD) is a quantification used to measure the speaker or writer's vocabulary. The larger the LD is, the more a speaker or writer is likely to have better linguistic capabilities, the bigger the speaker's competence and even the better the economic and social status he or she has (McCarthy, 2005). There are several ways of measuring lexical diversity. The previous American and Dutch research cited used such a method of measuring the ratio of the unique words or the "type-token ratio" TTR (number of unique words divided by the total number of words) (Templin, 1957). The Dutch research also indicates that this method gives a good impression but is not always reliable (Reuneker, Waszink & Van der Wouden, 2017). It turns out that the type-token ratio is influenced by the text length (Richards, 1987, Kettunen, 2014, Covington & McFall, 2010). When a text becomes longer it automatically contains more words that are the same, hence appearing frequently in the text. So, the longer the text is, the number of tokens increases, but the types (unique words) do not increase with the same amount. Thus, this method is not the most reliable one (Covington & McFall, 2010).

Koizumi explored the reliability of lexical diversity measurements with his 2012 study, which aimed to identify measures of lexical diversity that are least affected by text length and can be used to analyze short texts. He did this by comparing different measurements for lexical diversity, including the MTLD (Measure of Textual Lexical Diversity). This method looks at the relationship between the unique words and all words, which is done by taking a wide-ranging number of small excerpts from the text. The MTLD depicts the ratio of the total number of tokens in a text and the mean length in words of parts of the text where a TTR of 0,72 is valid. It takes ever increasing parts of the text until the TTR of 0,72 is reached for that part of the text. The total number of these parts of the entire text is the divider of the number of tokens. That result is taken for both the text in normal order and in reverse order. Then the mean of these two numbers is taken, which is the MTLD score. The reason the factor size of the TTR is 0.71 is because calibration studies show that this factor size number is the most reliable when calculating the MTLD score (McCarthy, 2005).

Koizumi also concluded that the MTLD method is least affected by text length (Koizumi, 2012). This has also been concluded by McCarthy and Jarvis who, examined the validity of the MTLD approach (McCarthy & Jarvis, 2010. They found that the MTLD method scores highest on all four validity points and therefore this method seems the most reliable (McCarthy & Jarvis, 2010).

3. Problem statement

In this research we study the following three hypotheses.

Hypothesis 1:

Women have a slightly higher MTLD-score than men. Women will score slightly higher than men when comparing the lexical diversity of their lyrics using a MTLD-score.

Hypothesis 2:

With age comes more lexical diversity, therefore there will be a positive correlation between the artist's age and their MTLD-score.

Hypothesis 3:

Artists who have a higher MTLD-score are more popular compared to artists with a lower MTLD-score.

4. Method

In this research we want to determine if there is a difference in lexical diversity in song texts between male and female artists, by giving artists a vocabulary-score using the MTLD method. To get a better understanding if an artist vocabulary has any influence on their popularity a comparison between MTLD-score and their popularity is made. In addition, we compared the MTLD-score to their age to see if there is a correlation between the two and if there are any gender differences.

4.1 Corpora

To investigate the lexical diversity of Dutch hip-hop artists, an analysis of their lyrics was set up using the MTLD method of McCarthy and Jarvis (2008), which is used to analyse short texts.

A corpus of twelve male and a corpus of twelve female artists is compiled. For compiling the male hip-hop artist, the most known hip-hop artist of the Netherlands has been used (NOS, 2018). This is because they made enough songs without any featuring artists, and therefore have enough lyrics to compile a corpus with the addition of getting a better understanding of popularity and MTLD-score it is the obvious choice to pick the most popular artists. Because there are only a few (known) female Dutch hip-hop artists (Reuneker, Waszink & Van der Wouden, 2017), they have been selected of a list from errday.nl [1] containing five female hip-

[1] The website errday.nl focuses only on lyrics of Dutch hip-hop artist but have a very narrow database and do not state where they get their lyrics from.

hop artists. When not on the list, we went to the male lyrics and searched if there was a female featuring artist on some male artist songs. If there was, it was made clear that these female artists have made a couple of songs alone (without any featuring artist) by searching the artist on genius.com[2]. If this was the case the female artists were used for this study. Nonetheless, when not finding any lyrics of female artists we searched if these artists were on Spotify or Apple-music and see if they had enough songs. This gave a total of twelve female hip-hop artists with enough songs, based on these twelve female artists we choose to only have twelve male artists to get an equal comparison.

After establishing which artists to use, the lyrics were conducted. Lyrics used for the corpus of each artist were mostly acquired from genius.com, when the song was unavailable on genius.com it was extracted from errday.nl, musixmatch.com or was self-transcribed. Furthermore, it was checked that the artist (duo or group) only appears alone in the songs, not featuring other artists, followed by choosing the songs from the list that is ordered by most searched for from genius.com from top to bottom, note that this can vary from time to time. Hence, the other platforms do not state this method, errday.nl puts the newest lyrics first wherefore musixmatch.nl sorts on most listeners per song. To set an average of tokens (words) that are used for each artist to make it a fair comparison, the artists whose lyrics could not be found were first transcribed. This gave a number of tokens that could not be increased with other lyrics of the artist. Within each lyric, choruses and pre-choruses that are the same through the entire lyric of the artist are only counted once per lyric, so artists are getting a fairer MTLD score. Which came to an amount of approximately 1500 tokens, with an aim of not cutting songs short and getting a fair MTLD-score a standard deviation of 100 tokens was set.

Additionally, being aware that the lyrics are not all purely Dutch (slang and some words in a different language), they are part of the expression and identity of the artist, and of their vocabulary wherefore these words have not been distracted from the lyrics (De Roest, 2017). The detailed table for the songs and artists that were used can be found in Appendix A.

[2] Genius.com hosts a cooperative online lyrics database, which refers to the method of crowdsourcing for their content to the database. Users of the website are encouraged to review and correct existing lyrics as well as transcribe new lyrics themself, by earning points and status, this collaborative form also applies to musixmatch.com.

4.2 Calculation of MTLD value

MTLD is calculated by sequencing the TTR score over the entire text. It is best described in the following flowchart that was published by McCarthy (2005).

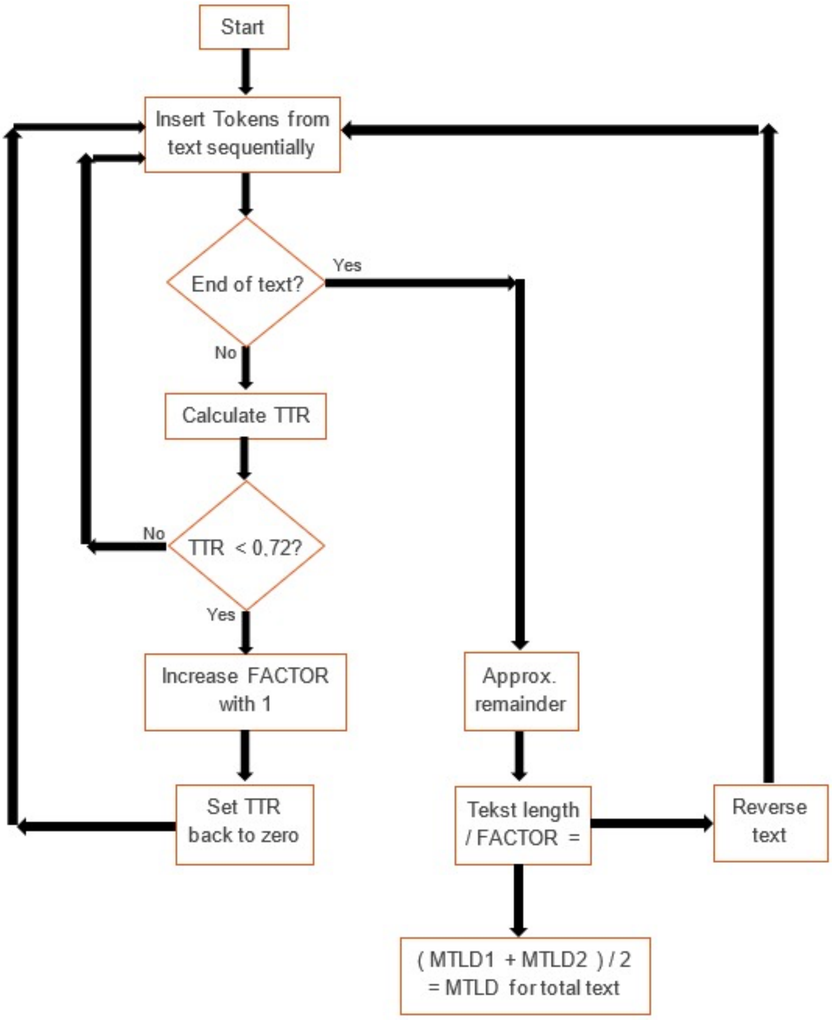

Figure 1; A flow-chart of McCarthy (2005) to explain how MTLD is calculated.

The MTLD is a measurement that is calculated using the number of times several words with a certain TTR exists within a text. To eventually get to the MTLD-score, the TTR is calculated for increasingly more words of the text. When the TTR drops below 0,72 the TTR is reset and the factor is increased with one. When the entire text is measured, the MTLD for this is the total text length divided by the factor resulting in a first MTLD score (forward processing). Then the text is scored a second time, but in reverse (backward processing), generating a second MTLD score. The total MTLD score is the average of these two. An example of this can be found in Appendix B, using an example sentence.

4.3 Measurements

To calculate the MTLD-score the Python programming language version 3.8.8 (python.org) is used and the natural language toolkit (NLTK) is added to the program. This toolkit is developed especially for Python and offers different methods and tools for text processing in different languages (nltk.org), this includes tokenization, parsing and many more.

Firstly, the lyrics are tokenized i.e., breaking up the lyrics into smaller units. In this case these units are the individual words in the lyrics, since this is the input to calculate the MTLD-score. After tokenizing the corpora, it is important to eliminate the capitals and punctuation marks because the program recognizes these as a unit and thus a word, affecting the MTLD-score.

To actually calculate the MTLD-score, lexical-diversity 0.1.1 (pre-programmed python program) is added to the tokenized python code. This is a simple program for calculating lexical diversity, by using the pre-programmed function: "ld.mtld_ma_bid", the function calculates the MTLD value. This toolkit allows for both forward and backward processing and then takes the mean value of these which is shown in Appendix B and Figure 1 (McCarthy & Jarvis, 2010).

After calculating the MTLD-score for the various artists, a t-test is done to see if there is a significant difference between the MLTD-score of male and female artists. Furthermore, to explain such a difference a linear regression is used to measure if age has an influence on artists MTLD-score. Another linear regression is used to analyze if an artist's MTLD-score has an effect on their popularity. Popularity being calculated by dividing the monthly listeners (on Spotify of the specific artist) by the number of years active (Appendix A). This is done based on the assumption that the longer an artist has been active, the higher the probability that they have amassed a larger audience. In this research, we call this the corrected popularity (Appendix A). Different methods of assessing an artist's popularity were used in other studies (e.g., Bellogin et al 2013, Ren & Kauffman 2017, Schedl 2011, Schedl 2019). Hence, there is no standard measure of popularity thus, we chose to construct our popularity measurement based on listeners. Because the study examines artists' lyrics, wherefore the assumption was made listeners at least listen to the lyrics of the artist with a possibility of streaming songs for other reasons.

In addition, for testing if MLTD-score has an effect on popularity the female artist S10 with an MTLD-score of 42.83 and a corrected popularity score of 558536 is removed from this test. This popularity score is probably due to her participation in the Eurovision song contest. Which is a yearly competition between mostly European countries about who has the best song and singer and is broadcasted worldwide on television. Therefore, S10 probably gained more listeners resulting in an abnormally high corrected popularity score for within this study.

5. Results

5.1 MTLD-score

Figure 2 shows the calculated MTLD-score per artist, as well with the average MTLD-score for female artists (pink), male artists (blue) and the overall average of the sample group (grey).

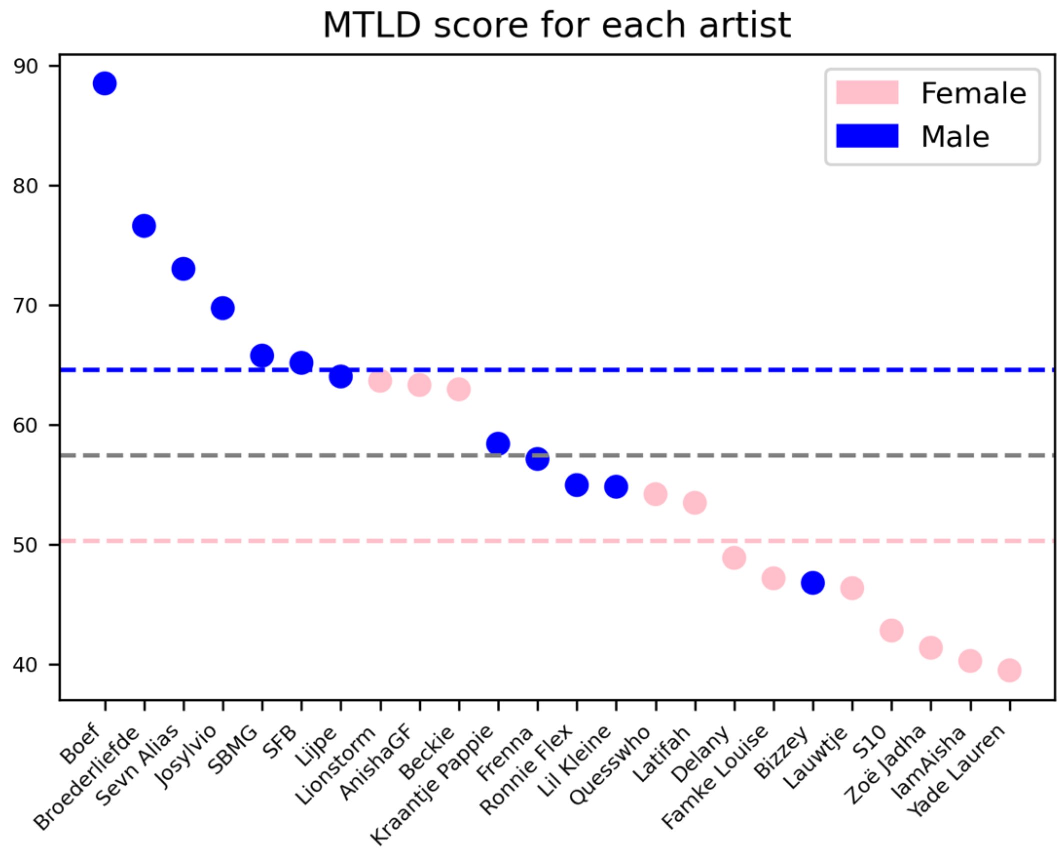

Figure 2; MTLD-score of each artist arranged in decreasing MTLD-score. The grey line is the average MTLD-score of all artist, blue is the male average and pink the female average.

T-test

To compare male artists MTLD-score to female artists MTLD-score an independent samples student t-test was performed. The male artist distribution and the female artists distribution were sufficiently normal for the purpose of conducting this t-test (i.e., skew <|0.2| and kurtosis <|0.6|(Schmider et al, 2010). The MTLD-score for both gender groups were normally distributed, as assessed by Shapiro-Wilk's test ($p > .05$). Additionally, the assumption of homogeneity of variances was tested and satisfied via Levene's F test ($p > 05$). A detailed table for this can be found in Appendix C. There was a significant difference in the MTLD-scores for male artists ($M = 64.60$, $SD = 11.34$) and female artists ($M=50.35$, $SD = 9.12$) conditions; $t(22)=3.39$, $p = 0.003$. Male artists have a higher MTLD-score than female artists, hence hypothesis 1 is rejected.

5.2 Age

The second hypothesis aims to test for an effect of age on the artists' MTLD-score. Gender is converted to a dummy variable which takes one for male and zero for female and added to the model as control variable. A Q-Q plot of the standardized residuals (N=24, Figure3) suggests that the residuals are normally distributed.

No association between the age of the artist and their MTLD-score was found, (B=-.37, SE = .38, p = >.05). As already observed in the above analysis, there was a significant association between gender and MTLD-score (B=15.09, SE= 4.29, p = <.05). Since there is no significance between artist age and MTLD-score hypothesis two is rejected. The results can be found in Appendix D.

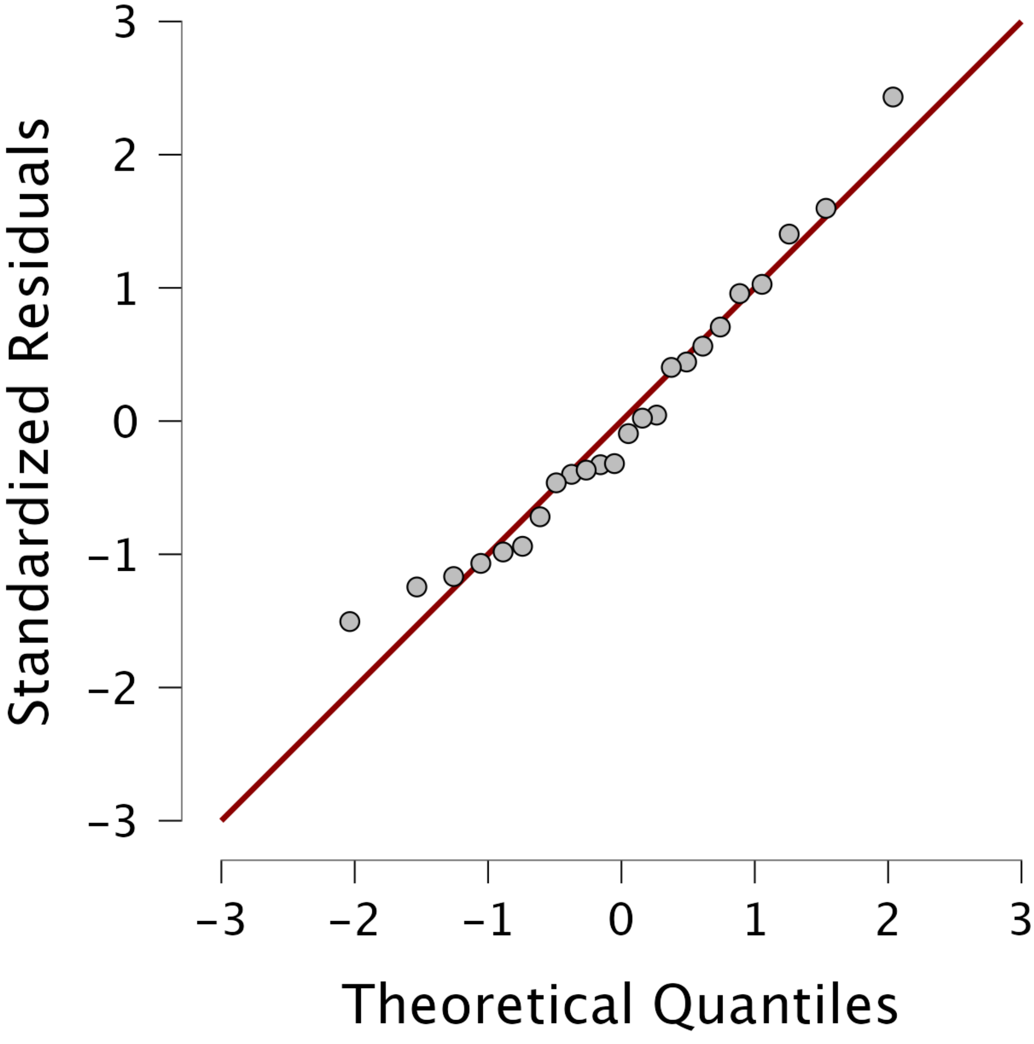

Figure 3. Q-Q plot of normal distributed data (N=24)

5.3 Corrected popularity

Lastly, to test hypothesis 3, a multiple linear regression is performed. As stated in method 4.3 the artist S10 was removed from this regression. In this test, a Q-Q plot of the standardized residuals (N=23, Figure 4) suggests that the residuals are normally distributed. Furthermore, it is found that artists' MTLD-score does not cause any statistically significant effect on artists' popularity (B= -1001.61, SE= 1084.79, p= >.05). Hence, hypothesis 3 is rejected. Which is also the case for the effect of artists' age on popularity (B= -621.71, SE= 1933.18, p= >.05). However, there was a statistically significant effect found for gender on the popularity (B = 125462.68, SE = 26217,25, p = <.05). An overview of the results can be found in Appendix E.

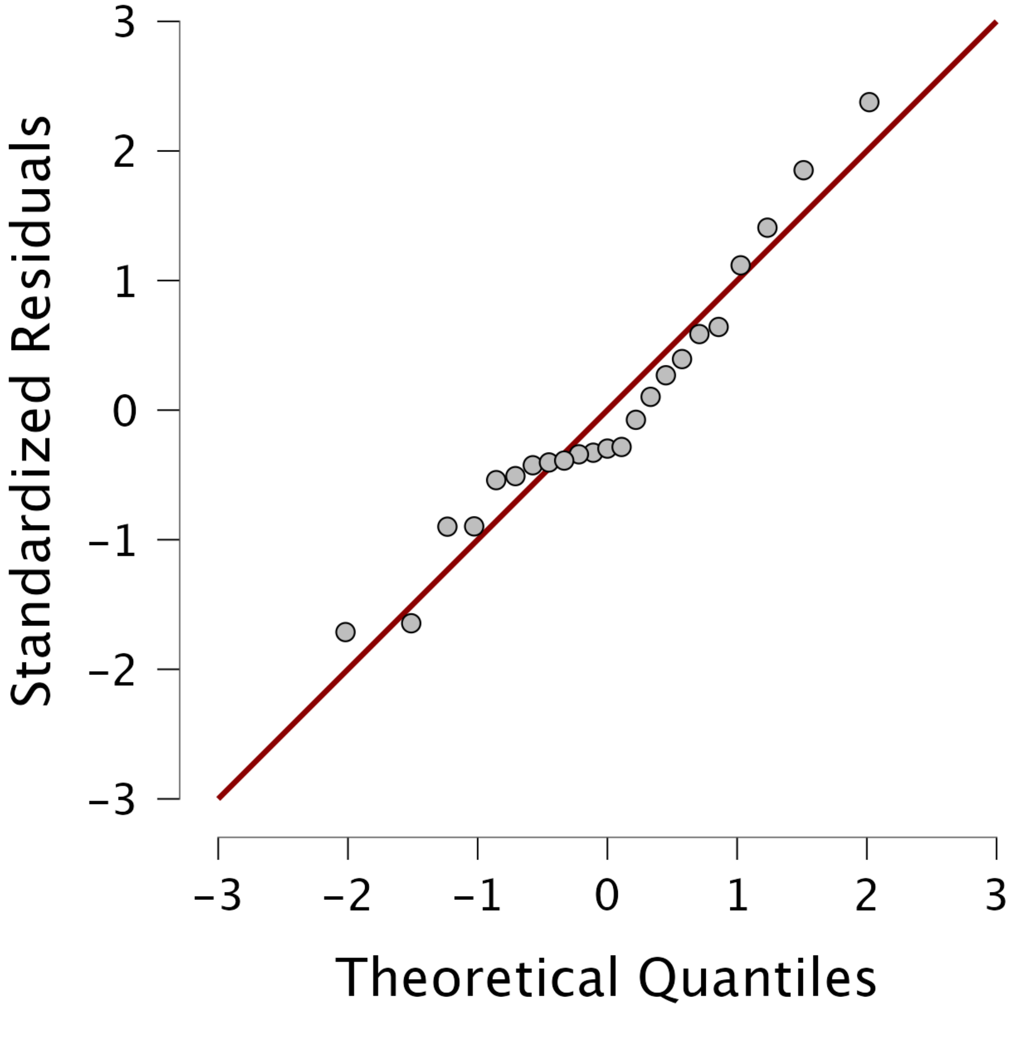

Figure 4. Q-Q plot of normal distributed data (N=23)

6. Conclusion and discussion

An important finding within this study is the lower average lexical diversity of the female artists in comparison to their male counterparts. A valid consideration for this could be the fact that not all artists write their songs all by themselves. For some artists these co-writers can be found on the lyric website genius.com. Furthermore, a lot of the corporate writers are working for both sexes, which could explain why some of the artists are having an adjacent MTLD-score. Another element to acknowledge is the fact that the record label often determines the broad outlines of the songs. Therefore, it can be implied that not every artist has all the lyrical freedom they want or deserve. A third reason why male artist score higher with the MTLD-score is when looking at the history of how hip-hop came to the Netherlands the founders are all male (Markus, van der Hoeven, & Verboord, 2012), which gives the indication of the time male hip-hop artist had to develop themselves and establish what Dutch hip-hop with taking the lyrics into account should be. Nevertheless, it is important to take into account that the Dutch hip-hop scene can be more difficult for women to enter than it is for men (de Roest, 2017), wherefore this could be an effect of females' lower MTLD-score.

When testing if artists' age affects their MTLD-score no statistically significant effect was found. Which is an unexpected finding, when there is different research stating that lexical diversity should be improving with age (Sullivan & Brown, 2015). To clarify this finding artist lexical diversity can also depend on their childhood reading activities (and social background) (Sullivan and Brown 2015). A clarification could be the age of their co-writers and the consideration of the change in co-writers. In addition, if the artist or their record label are established songwriters of popular songs, there is no need for improving the lexical diversity of the songs.

For the last hypothesis, it is shown that there is a correlation between popularity of an artist and gender. Wherefore, male hip-hop artists in the Netherlands are more popular than their female counterparts. It is important to recognize that female artists became part of Nederhop many years after the emerge of the genre (Markus, van der Hoeven, & Verboord, 2012). Thus, it is a logical suggestion that they had a shorter amount of time to develop themselves and gain popularity compared to the male hip-hop artists.

When in search of an influence of artists MTLD-score on their popularity there was no statistical correlation. Thus, within this research we cannot say that a higher MTLD-score influences artists' popularity. It is to say that there are other factors with a high influence on popularity such as the music beat, worldly known shows, live television, etc. (Schedl, 2019). Another explanation of why it is often male artists who have the higher popularity score could be that it is "easier" for male artists to gain listeners compared to female artists. Assuming it is probably still easier to enter the hip-hop scene for them.

7. Research limitations and future research

During the process of this research, some limitations have been observed. One of the main limitations is data availability especially when it comes to finding lyrics of Dutch female hip-hop artists. There are a lot of male Nederhop artists, but when looking for female artists, it was clear the genre has very few of them that have enough exposure to find them. There are probably more unknown Dutch female hip-hop artists that exist, that maybe get a better MTLD score but do not have enough exposure on, for example, Spotify or YouTube. So they are hard to find. Due to the scope of this study, it was unrealistic to search for such undiscovered Nederhop artists. Additionally, some female Nederhop artists were not used due to the lack of (Dutch) songs of their own making. Another limitation is the sources that are used for getting the artist's lyrics. These sources (genius.com, errday.nl, musimatch.com) are all relying on people who transcribe the music. This can result in some poorly transcribed lyrics, wherefore you can argue if the artist really sings (or means) what is transcribed.

Nonetheless, taking the above into account there are still multiple directions in which this research may go, to get more extensive knowledge. Firstly, the results indicate there is a statistically significant difference between the MLTD-scores of the genders. A direction for future research could be investigating this phenomenon by studying if this occurs with other music genres as well such as; pop, country, rock etc. This can be done for Dutch artists, or Dutch performing artists but also for other countries and other languages. This can give the possibility of comparing the genre's MTLD-scores by gender and country or language to see which country or language has the artists with the highest MTLD-scores sorted by gender.

A second direction this research may go, is investigating if artists' vocabulary improves over a longer time, by comparing their lyrics from their starting years with lyrics of their later years. This can give an insight if artists' vocabulary will improve over time or stay the same. Wherefore such results can perhaps indicate if the artist's increase in popularity could be explained by their increased lexical diversity over time.

Lastly, to point out the limitation of the shortage of female Nederhop artists, it might be of value to determine if there is a demand for female Nederhop artists among the audience. And whether or not, the audience's opinion can be changed by the vocabulary-score of the artists. With this insight, artists and producers have more knowledge of what to do to increase the audience, the popularity and the success of artists.

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Appendix A

Male artist

Artist	MTLD-score	Age (may)	Starting year	Songs	Monthly listeners (may)	Corrected Popularity
Bizzey	46.81	37	2010	Cry Aventura Girl You Know Pull up Doe het voor Gunman Op de vlucht	2.077.696	173141
Boef	88.53	29	2015	Sofiane Range Sessie	1.427.675	203954
Broederliefde	76.63	22 (Average)	2012	Tizora Spontaan Officieel Nightvision	1.145.877	114588
Frenna	57.16	30	2014	Only you Langste sms Door t lint Capuchon Waistline	1.713.388	214174
Josylvio	69.76	30	2014	Catch up Ride or Die Gimma Zoveel Takkies	1.307.632	163454
Kraantje Pappie	58.43	35	2007	Lil caraney Pompen Feesttent Vellende ster Wat de nacht ons brengt	1.541.178	102745
Lijpe	64.05	28	2010	Eng Doe rustig Was er nooit	802.524	66877
Lil Kleine	54.84	27	2005	Nog steeds aan Regen Alleen Rook	2.283.242	134308
Ronnie Flex	54.98	30	2008	Combinaties Tankstation Weiland Eiland In een jet	2.840.348	202882
SBMG	65.79	27 (Average)	2012	Wagman Im in Love with a Huzla Kloezoe Hard gaan	625.977	62598
Sevn Alias	73.04	25	2014	Tiësto Migos Duw Location	1.188.336	148542
SFB	65.19	28 (Average)	2013	Appel Murderer Jij kan chillen met mij Rutte	1.052.870	116986

Female artist						
Artist	**MTLD-score**	**Age (May)**	**Starting year**	**Songs**	**Monthly Listeners (May)**	**Corrected Popularity**
AnishaGF	63.34	19	2019	Hoodboy 77 Barz	26.373	8791
Beckie	62.98	35	2013	Karma Kapot Champagne Beng Beng Liever	3.403	681
Delany	48.9	22	2016	Basic Wannabe Ik beloof t Whine up Gemini Ik voel je Mood Hulp van boven	140.652	23442
Famke Louise	47.19	23	2016	Op me Monnie Slangen High Derriere Boss Bitch Haters Herboren zelf	254.925	42488
IamAisha	40.29	44	2010	Goed genoeg Moordenaar Missie 13 Late Night Dresscode Hey Boy	95.390	7949
Latifah	53.5	29	2014	Gewaarschuwd Gunshot Papa Kijk ze nu dan	454.572	56833
Lauwtje	46.37	29	2018	Elastisch Dripstar Vermogen Straight Dag in, dag uit	125.384	31346
Lionstorm	63.68	28 (Average)	2018	WTJDZ No h8ro Emo Track Vies Snekis	9.068	2267
Quesswho	54.21	27	2017	Kwijt Met die Bitch I know Next move Niet bij mij 401	50.731	10146
S10	42.83	21	2017	Adem je in Diamonds Laat mij niet gaan Vleugels Zonder reden Gelogen Alleen	2.792.678	558.536
Yade Lauren	39.5	23	2016	In de nacht Papa Met jou Niet die bitch Insane Lonley	934.203	155701
Zoë Jadha	41.39	20	2017	Barz Coach je vriendin Gucci op me body Dillema Regular shit	18.931	3786

Appendix B

Example of forward and backward processing for calculating the MTLD-score by using the following sentence:

"The cat chased the mouse up the stairs and sat waiting for it for two hours. The mouse stopped moving above the stairs.".

Text	TTR	< or > 0,72?	Factor
The	1.00	>	0
The cat	1.00	>	0
The cat chased	1.00	>	0
The cat chased the	0.75	>	0
The cat chased the mouse	0.80	>	0
The cat chased the mouse up	0.83	>	0
The cat chased the mouse up the	0.71	<	1
The cat chased the mouse up the stairs	1.00	>	1
The cat chased the mouse up the stairs and	1.00	>	1
The cat chased the mouse up the stairs and sat	1.00	>	1
The cat chased the mouse up the stairs and sat waiting	1.00	>	1
The cat chased the mouse up the stairs and sat waiting for	1.00	>	1
The cat chased the mouse up the stairs and sat waiting for it	1.00	>	1
The cat chased the mouse up the stairs and sat waiting for it for	0.83	>	1
The cat chased the mouse up the stairs and sat waiting for it for two	0.86	>	1
The cat chased the mouse up the stairs and sat waiting for it for two hours	0.86	>	1
The cat chased the mouse up the stairs and sat waiting for it for two hours The	0.89	>	1
The cat chased the mouse up the stairs and sat waiting for it for two hours The mouse	0.90	>	1
The cat chased the mouse up the stairs and sat waiting for it for two hours The mouse stopped	0.91	>	1
The cat chased the mouse up the stairs and sat waiting for it for two hours The mouse stopped moving	0.92	>	1
The cat chased the mouse up the stairs and sat waiting for it for two hours The mouse stopped moving above	0.92	>	1
The cat chased the mouse up the stairs and sat waiting for it for two hours The mouse stopped moving above the	0.86	>	1
The cat chased the mouse up the stairs and sat waiting for it for two hours The mouse stopped moving above the stairs	0.87	>	1
Text has 23 words. 23 divided by 2 equals an MTLD1 of 11 with a remainder 1.			

Text	TTR	< or > 0,72?	Factor
Stairs	1.00	>	0
Stairs the	1.00	>	0
Stairs the above	1.00	>	0
Stairs the above moving	1.00	>	0
Stairs the above moving stopped	1.00	>	0
Stairs the above moving stopped mouse	1.00	>	0
Stairs the above moving stopped mouse the	0.86	>	0
Stairs the above moving stopped mouse the hours	0.86	>	0
Stairs the above moving stopped mouse the hours two	0.89	>	0
Stairs the above moving stopped mouse the hours two for	0.90	>	0
Stairs the above moving stopped mouse the hours two for it	0.91	>	0
Stairs the above moving stopped mouse the hours two for it for	0.83	>	0
Stairs the above moving stopped mouse the hours two for it for waiting	0.85	>	0
Stairs the above moving stopped mouse the hours two for it for waiting sat	0.86	>	0
Stairs the above moving stopped mouse the hours two for it for waiting sat and	0.87	>	0
Stairs the above moving stopped mouse the hours two for it for waiting sat and stairs	0.81	>	0
Stairs the above moving stopped mouse the hours two for it for waiting sat and stairs the	0.76	>	0
Stairs the above moving stopped mouse the hours two for it for waiting sat and stairs the up	0.78	>	0
Stairs the above moving stopped mouse the hours two for it for waiting sat and stairs the up mouse	0.74	>	0
Stairs the above moving stopped mouse the hours two for it for waiting sat and stairs the up mouse the	0.7	<	1
Stairs the above moving stopped mouse the hours two for it for waiting sat and stairs the up mouse the chased	1.00	>	1
Stairs the above moving stopped mouse the .hours two for it for waiting sat and stairs the up mouse the chased cat	1.00	>	1
Stairs the above moving stopped mouse the .hours two for it for waiting sat and stairs the up mouse the chased cat the	1.00	>	1
Text has 23 words. 23 divided by 1 equals an MTLD1 of 11 with a remainder of 1.			

Appendix C

Independent Samples T-test

	t	df	p	Mean Difference	SE Difference
MTLD	3.392	22	3	14.251	4.201

Assumption Checks

Test of normality (Shapiro-Wilk)

		W	P
MTLD	Male	0.969	0.905
	Female	0.887	0.109

Test of Equality of Variances (Levene's)

	F	df_1	df_2	p
MTLD	0.141	1	22	0.711

Descriptives

Group Descriptives

	Group	N	Mean	SD	SE	Coefficient of variation
MTLD	Male	12	64.601	11.342	3.274	0.176
	Female	12	50.350	9.119	2.633	0.181

Appendix D

Descriptives

	N	Mean	SD	SE
MTLD	24	57.475	12.421	2.535
Age	24	27.875	5.826	1.189
Gender	24	0.500	0.511	0.104

Coefficients

Model		Unstandardized	Standard Error	Standardized	T	P
H0	(Intercept)	57.475	2.535		22.669	<.001
H1	(Intercept)	60.335	10.483		5.755	<.001
	Age	-0.373	0.376	-0.175	-0.993	0.332
	Gender	15.091	4.287	0.621	3.520	0.002

Appendix E

Descriptives

	N	Mean	SD	SE
Popularity	23	89029.522	73842.744	15397.277
Age	23	28.174	5.766	1.202
Gender	23	0.522	0.511	0.106
MTLD	23	58.112	12.293	2.563

Coefficients

Model		Unstandardized	Standard Error	Standardized	T	P
H0	(Intercept)	89029.522	15397.277		5.782	<.001
H1	(Intercept)	99292.275	87017.211		1.141	0.268
	Age	-621.714	1933.182	-0.049	-0.322	0.751
	Gender	125462.679	26217.250	0.868	4.786	<.001
	MTLD	-1001.605	1084.789	-0.167	-0.923	0.367