DECODING SOFT: gen z soft masculine menswear trends through semantic network analysis

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Abstract

With the sprouting of social media in recent years, new menswear tribes have emerged – *e-bois*, *sad boys* & *softboys* among Generation Z. This study examines menswear trends over 10 years through semantic network analysis on Orange3 machine learning. We aim to debunk *soft* masculinity in high-end fashion popularised by Gen Z cultures which differ from dated concepts such as *androgyny* and *metrosexual*. Through semantic network analysis, we quantified i) dominant design trends, ii) examined the connective power of trends under the degree of centrality and iii) studied the correlation between concepts. Our results revealed dominant trends in menswear with their corresponding design. The methods of this study overcome human-based forecasting's predispositions by analysing 3,047 menswear collection reports from Vogue US via machine learning combining technological efficiency with human ingenuity. Our research points to contextualising menswear trends into semantic structures reinforced by quantitative and qualitative analysis. Our study demonstrates the feasibility of using machine learning for organising design trend concepts, recognising patterns, fashion forecasting, academic research, and potentials as an ideation tool for the creative industry.

Introduction

In recent decades, gender has become increasingly blurred (Clarion-Ledger, 2014, Andersen, 2004)), especially among Generation Z (Gen Z) who liberate themselves from binary systems (Stylus, n.d.). Social media (SM) has further incentivised these shifts (Vivienne, 2017). Gen Z has also become the main demographic consumer group with 97% of Gen Z relying on SM for fashion purchase inspiration (Kastenholz, 2021). TikTok, a video-led SM, has gained immense traction among Gen Z youth due to its abundant video content that entices greater engagement than Facebook, Instagram, & Twitter (Doyle, 2021).

Gen Z is predisposed have greater sociocultural awareness than previous generations (Thomas, 2021). Recent SM discussions have raised concerns about dated male hegemony and its detrimental effects as toxic masculinity (TMAS) (Parent et al., 2019). In response, Gen Z men on TikTok dress with the same fluid freedom women have in order to break up these stereotypes. Fashion brands have correspondingly introduced *soft* elements into mainstream menswear in order to meet the needs of Gen Z (Cohn, 2020). Jung coined soft Masculinity (SMAS) to illustrate *softer* masculinity that embraces male/female qualities but still identifies as binary male (Jung, 2009). Gender fluidity points to an individual with a fluxion gender. WGSN trend forecast (WGSN, 2015a) initially reported manifestations of Gen Z SMAS in 2015. Gen Z have skilfully embraced other youth subcultures i.e., emo, skater, gaming and Pan-Asian SMAS, consequently forming new *soft* tribes - *E-bois*, *softboys* & *sadbois*. TikTok has helped brought unprecedented attention to these communities (Luna and Barros, 2019, Fraser, 2020, Commetric, 2019).

However, men embarking on femininity is not new-fangled and has been extensively studied in fashion as *androgyny* (Reilly, 2020), *metrosexual* (Simpson, 2002), and *cross-sexual* (Lee et al., 2020a), which points to complex expressions of internal/external identity, sexuality and differs from pop-culture focused SMAS. Studies on SMAS have been conducted under the guise of Asian pop-culture i.e., K-pop (music) yet little has been done to study how contemporary fashion interprets SMAS and how its design components work alongside traditional MAS trends.

In this study, our aims are to i) examine how contemporary high-end menswear designers are interpreting the *soft* styles of Gen Z, ii) identify which trend keywords are dominant in menswear and iii) how they correlate through the degree of centraility (DC). The methods of this study overcome the biases of human-based forecasting by analysing 3,047 MW collection reports from Vogue on a machine learning platform (Orange3), combining technological efficiency with human ingenuity. Our findings delineate SMAS menswear trends in Western society. We have also demonstrated the feasibility of this methodology for organising trend concepts and patterns for fashion forecasting.

Literature Review

Traditional masculine identity through dress

Traditional beliefs have cemented men playing dominant roles relating to the primacy of work and leadership (Benokraitis, 1996), which has influenced our dressing practices.

Masculine (MAS) features typically demonstrate male hegemony (Table 1) (Davis, 2013, Miller-Spillman and Reilly, 2019). These qualities are expressed through colour, fabric, garment detailing and pattern (Barnes and Eicher, 1992).

Author/code	*Garment*	*Silhouette*	*Textures*	*Patterns*	*Colour*	*Theme*
Buckley & Fawcett (2001)	T-shirts Oxford shirts Crew sweaters Polos & rugby jerseys		Twills Drills Worsted wool Traditional suiting fabrics	Argyle Plaid	Blues Sombre dark colours Monoc	Casual W
Davis (2013)	Black leather jackets Military jackets Severe tailoring Classic male trousers & shorts	Padded & exaggerated shoulders	Heavy tweeds Flannels Corduroy Workwea	Houndsto Pin		
Miller-Spillman & Reilly (2009)	Jumpsu S					

Table 1. Menswear dress features

New cultural landscapes in menswear

Menswear at-large has held a restrained aesthetic (Davis, 2013) contrary to female gender norms subverted through sportswear (Lee-Potter, 1984), power dressing (Entwistle, 2020) and androgynous styles (Miller-Spillman and Reilly, 2019), e.g., Saint Laurent's Le Smoking & Chanel's garçonne style (Davis, 2013). However, men of the past have also transcended prevailing gender expectations through fashionable dress; Brummell, Dandyism, hippie psychedelia, pop icons such as Boy George & Leigh Bowery inspiring 80s Ravers, Mah-Jong tights & tunics (Eldvik, 1988) and slim-fitted jumpsuits & man-skirts (H&M 2002, Yves Saint Laurent, Jean-Paul Gaultier & Marc Jacobs 2009) to Dior Homme by Slimane (Arnold, 2001). Though, such dressing practices have not been adopted by male consumers at-large in Western countries due to stigmas attached to feminine men (Hollander, 2016).

Fashion designers are fuelling these discourses by questioning if clothes are gendered (Zahm, 2017, Trebay, 2015, Commetric, 2019, Razak, 2019, Wightman-Stone, 2016, Cohn, 2020).

Influenced by Far-eastern pop culture, designers have used the runway to disseminate Gen Z TikTok *soft* trends into Western mainstream consciousness in response to TMAS (Friend, 2018, Singh, 2020). TMAS has been used to refer to outdated ideals psychologically harmful to men and the greater society (Legg, 2020). Fluid dress encourages men to break up stereotypes by communicating sensitivity similar to their female counterparts. Jung first coined soft masculinity (SMAS) to illustrate a hybridisation of male/female identities who embellished themselves with an elaborate dress (Jung, 2009) and distinguished themselves from cross-sexual (Lee et al., 2020a) & metrosexual (Simpson, 2002). In recent years, SMAS has been re-established by the media as a style that originated from runway collections where men are granted the same measure of freedom to express identity previously exclusive to women (Singh, 2020, Laux, 2021, Napoli, 2020). In MW, "Feminine" designs, colours, floral patterns and see-thru tops are increasingly seen on the runway. Moreover, makeup & beauty products aimed at male consumers have become commonplace, which was not long before a taboo (Singh, 2020). Gen Z youth tribes such as *soft boys* are proponents of such ideas and are responsible for re-defining future MAS (Yotka, 2018).

SMAS is not limited to dressing practices only and differs from other MAS conceptions by presenting friendliness, kindness, and non-intimidating behaviours (Louie, 2012). It is a hybrid product of pop cultures - Korean flower boy, Japan's bishonen and global metrosexual MAS. This female-friendly man is perceived as more fitting for our globalised society conceptualised through K-pop music, TV dramas, SM, and fashion styling (Ainslie, 2017).

Though feminine in nature, SMAS differentiates itself from androgynous individuals (Reilly, 2020) & nonconforming genders: gender-fluid, agender, bi-gender & genderqueer (Zambon, 2020, Butler, 2004). These terminologies describe the combination of inward/outward expressions of identity and how one perceives themselves, thus not pertinent to studying fashion tribes (Table 2).

Terminology	Definition
Metrosexual (Simpson, 2002)	Heterosexual men with disposable income that are conscious of their outward appearances, who may resort to excessive grooming & feminine fashio express trend-consciousness rather than sexuality or gender
Crosssexual (Lee et al., 2020a)	Heterosexual men that wear garments with traditional
Androgyny (Reilly, 2020)	Ambiguous gender express
Nonconforming gender terms (Butler, 20	Such gen s

Table 2. Menswear culture terminology & definitions

SMAS fashion tribes

Style tribes are traditionally bound to youth cultures that rebel against the governance of fashion elites (Polhemus, 2010). Globalisation and technology have eased the process for newtribes to form (Jennings, n.d.). The accumulative consumption of East Asian pop-cultures originating from Japanese manga has resulted in SMAS tribes (Jung, 2009). This cultural hybridisation has assisted K-pop to accumulate mass regional followings expanding their fanbase (Jung, 2009).

Global SM communities like TikTok is rife with SMAS due to its inclusiveness of diverse youth subcultures and has thus eased itself into mainstream consciousness. TikTok's popularity among Gen Z SMAS is attributed to factors including their digital nativism and preference to consume rich video formatted content, which tends to draw higher engagement compared withFacebook, Twitter or Instagram (Doyle, 2021). On TikTok, Gen Z develops individual identities, rejects pre-existing stereotypes, and opens up a global community's fluidity (Muliadi, 2020). More importantly, TikTok provides users with instant gratification by offering an intuitive platform to perform short lip-sync videos to their favourite pop idols or participate in dance competitions forming online communities (Thomas, 2021). Hollander (2016) has also observed men to have somewhat embraced mutable female dressing habits. Though, she argues distinctive feminine features remain taboo in association with men's dress. SMAS prompted by Gen Z, however, diverges from Hollander's theory calling for re- evaluation.

TikTok interactive features have incentivised SMAS portrayals among Gen Z youth claiming 800 million monthly users (Marci, 2020). SMAS initially emerged in fashion reports (WGSN, 2015a, WGSN, 2015b, WGSN, 2016, Stylus, 2016) and publication Dazed (Wang, 2016), but not entirely conceived as Softboys and other incarnations till 2018 (Figure 1).

Distinct cultural stimuli influence these tribes. The *Sad boy* concept is a melting pot of SMAS styles but does not attempt to disrupt gender expectations (Wang, 2016). *Softboys* are artistic, sensitive men with subtle hints of femininity, an older cousin of *E-bois* (Yotka, 2018, David, 2019). *E-bois* are driven by digital pursuits, including SM, gaming-related subcultures (anime, cosplay), Twitch (interactive steaming service) and champions gender fluidity (Marci, 2020, Bassil, 2019).

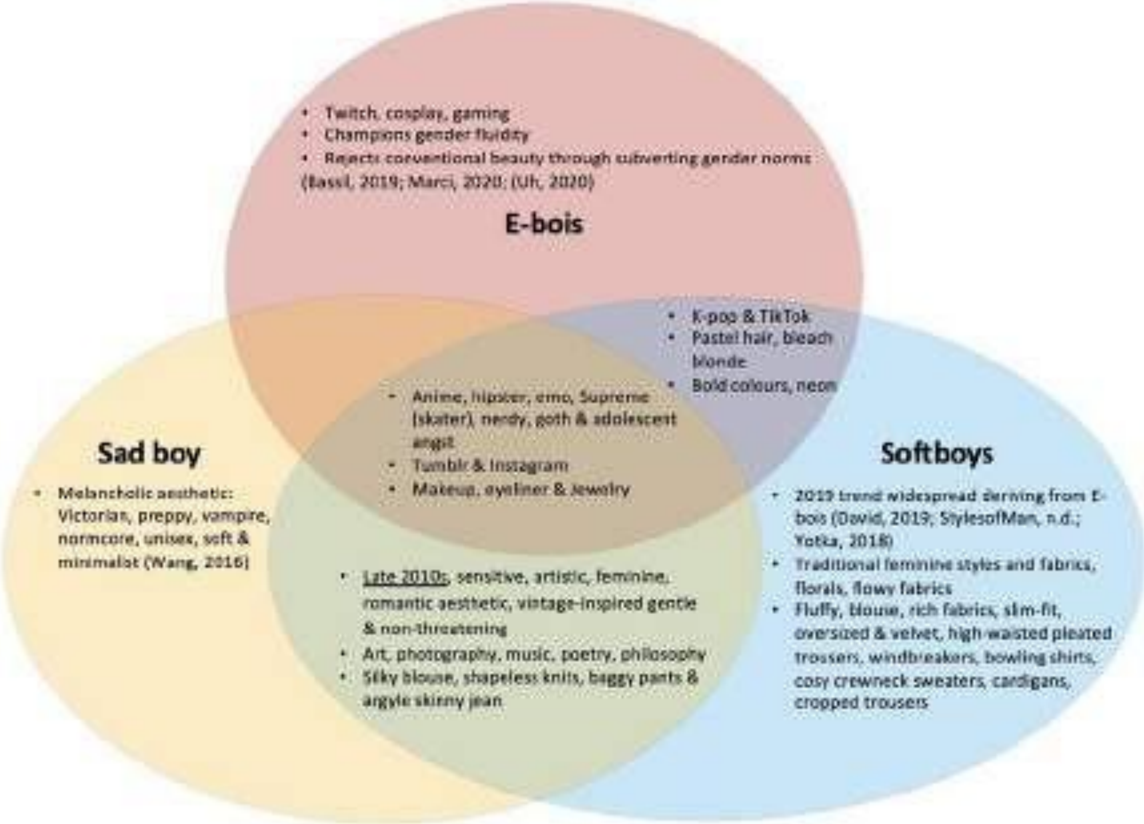

Figure 1. SMAS tribes & classifications manifested on SM

Current SMAS studies remain fixated on Asian pop idols' gender subversion (Ota, 2015, Lee et al., 2020b) and fan sentiment (Ayuningtyas, 2017). Our research purposes are to i) examine how contemporary menswear is interpreting *soft* style of Gen Z, ii) what design features are dominant, how they relate to other trends and iii) which *soft* trends are dominant. The contributions of this study include the use of machine learning methodologies to analyse fashion trends instead of manual analysis that is often skewed to the author(s) opinions. Our study will objectively identify the latest developments in MW under the influence of Gen Z culture and examine how MAS identity is interpreted through fashion trends on runway shows.

Big data in trend forecast

Trend forecasting predicts style developments and anticipates consumers' desires (Rousso and Ostroff, 2018). Designers consider trends to maximise appeal to their target audience through colourways, patterns, fabrics, design details and silhouettes (Jackson, 2007, Rousso and Ostroff, 2018). However, human-based forecasting, i.e. WGSN (WGSN, 2021), is often limited to idiosyncratic observations and does not objectively reflect market trends (An and Park, 2020). In recent years, retailers have incorporated big data analytics for forecasting (Chaudhuri, 2018), i.e., EDITED (EDITED, 2021). The authority to validate trends have thus loosened from producers to consumers (An & Park, 2020). Big data has been swiftly used by retailers to identify consumer behaviours and potential markets (Grammenos, 2015, Gaimster, 2012), likewise in academia (An and Park, 2020, DuBreuil and Lu, 2020). However, limitations remain: i) biased user data, ii) does not answer trend "whys" or "how", iii) outlier can affect results, iv) security issues, and v) small data remains more effective for practical, real-world learnings (Yamaguchi, 2015). Moreover, big data's complexity limits its efficiency (Kubick, 2012). It requires other processes, structuring, and analysis into context to be useful (Yamaguchi, 2015). Human-based methods consider complex factors in design (creativity & societal attitudes) which is inimitable by technology (Barnes and Lea- Greenwood, 2010). Therefore, big data will not replace traditional methods any time soon (DuBreuil and Lu, 2020). Finding an equilibrium between technological use with human ingenuity remains a promising area of study.

Contextualising fashion keywords

Past studies have suggested natural language processing for fashion forecasts (An and Park, 2020, Beheshti-Kashi et al., 2015). The semantic analysis examines the context surrounding text to accurately disambiguate the proper meaning of keywords (Sowa, 1987). Via such methods, one can draw from multiple channels to identify interacting ideas in a network (Drieger, 2013). SNA machine learning toolkits like Orange3 data mining provides an efficient platform with algorithms that can analyse human speech through predicate logic (Indurkhya and Damerau, 2010) and does not require complex coding skills. A key advantage includes the ability to extract valuable information from unstructured data and achieve human-level precision while remaining unbiased – unattainable by human-based/big data methods alone. Through SNA, we can quantify design trends by identifying the frequency of occurrence (FO), measure the DC value which stresses the most central feature of our network and outline the correlations between design features in a network (Golbeck, 2013).

FO allows researchers to pinpoint the number of times a word appears in a dataset revealing social patterns (Al-Hashemi, 2010, Callon et al., 1983). This novel study examines MW trends by collating catwalk reports transcribed with various perspectives alongside machine learning technology. The significance of this research lies in the quantification of semantics through our workflows which contextualises independent keywords to examine SMAS development.

Methodology

Data collection

This study used Orange3 data mining version 3.28 to analyse MW trend development. We conducted content analysis via collections of articles from Vogue US (Vogue, 2021), a key fashion resource provider and studied how MW evolved on the catwalk through trend and language describing the formation of SMAS. These online resources are readily accessible, provide real-time feedback akin to SM, and are appropriate to analyse from in our increasingly digitalised environments.

We collected 3,047 MW reports from fall 2012 to spring 2022 (20 seasons) from the "Big 4" fashion weeks New York, London, Milan, and Paris. Spring 17 had the highest number of participating designers, with spring 21 least (Figure 2). During this period, there was only 1 capsule collection (pre-fall). Due to the limited collections (10) shown, its irregularity is inconsistent with the rest of our data and thus was not incorporated in our final dataset. Pre-collections were traditionally capsule collections that linked the principal bi-annual shows to satisfy consumers with international lifestyles, which was often not seen as a commercial necessity in menswear (Dhillon, 2018). Moreover, collections that showed menswear and womenswear concurrently were also omitted from our dataset because we were solely interested in analysing MW only.

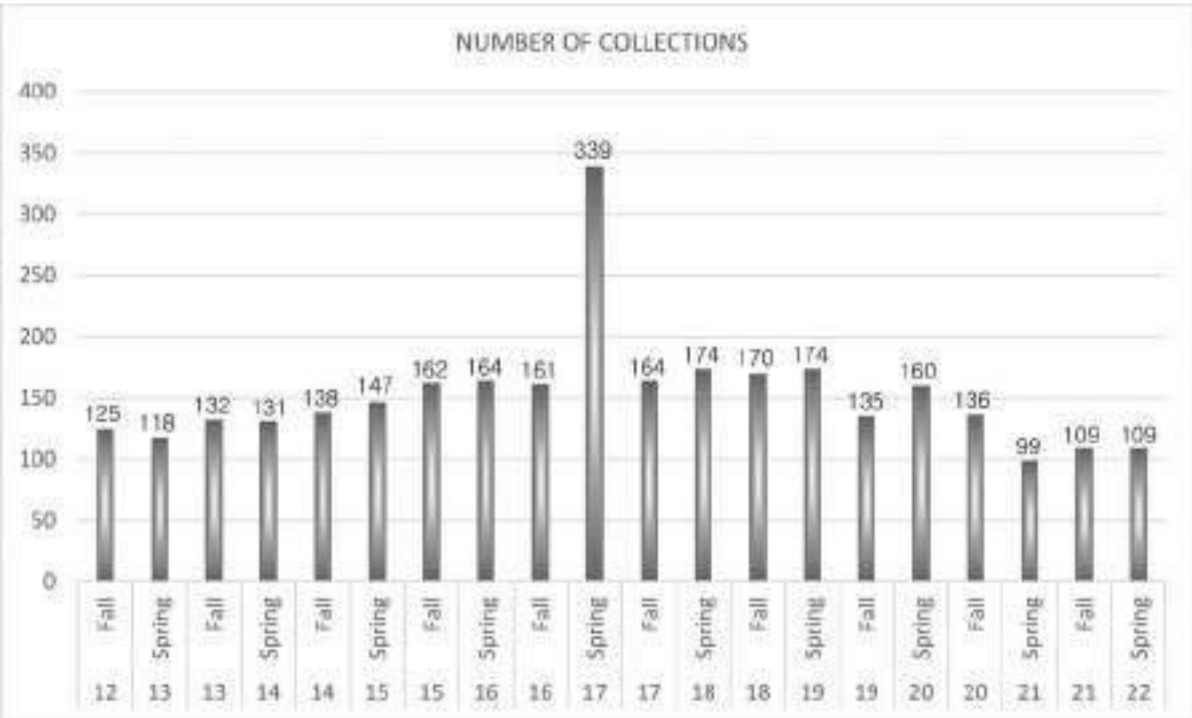

Figure 2: Number of participating collections per season during fall 2012 to spring 2022

Coding rules

Through reviewing established fashion literature and articles (Davis, 2013, Rousso and Ostroff, 2018, Miller-Spillman and Reilly, 2019, FIT, 2020, Ellinwood, 2021, An and Park, 2020, DuBreuil and Lu, 2020), we have devised an efficient design feature categorisation which better represents the complexities of design features and arrangements (Table 3). Precedent studies sometimes have ambiguous classing of features that do not encompass all possible variables in fashion design.

Design element	Criteria	Examples
Garment	Labels a garment item that is used to clothe the body (Ellinwood, 2021)	*Outerwear, tailoring, carg corset, et*
Silhouette	The outline of a whole garment and the most obvious visual element of a garment. Silhouettes evolve to accentuate or exaggerate different parts of the body (Burke, 2011)	*Bodycon, s*
Textiles	Describes tactile and visual surface qualities, appear and feel of a material or fabric (Ellinwood, Also, indicating fabric weight and	
Patterns	Repeated or one-off surface designs t woven into a fabric or printed on	
Colour	One of the most promin overall appea	
Theme	The import clothing is a	

Table 3. Coding rules

Data refinement through machine learning on Orange3

Figure 3. illustrates how designated articles were uploaded and processed on Orange3. We pre-processed our articles before they were ready for further analysis. 3,047 articles were uploaded onto Orange3 via the import documents widget, and through the corpus viewer widget, these articles could be accessed. The pre-process text widget is used to refine our unstructured text data. It assists in filtering meaningless and irrelevant words through a stop word file. Furthermore, it allows us to refine the text further by removing punctuations & numbers, unifying plural forms & abbreviations of words (e.g., pink & pinks), and removing verbs due to their insignificant role in expressing content meaning.

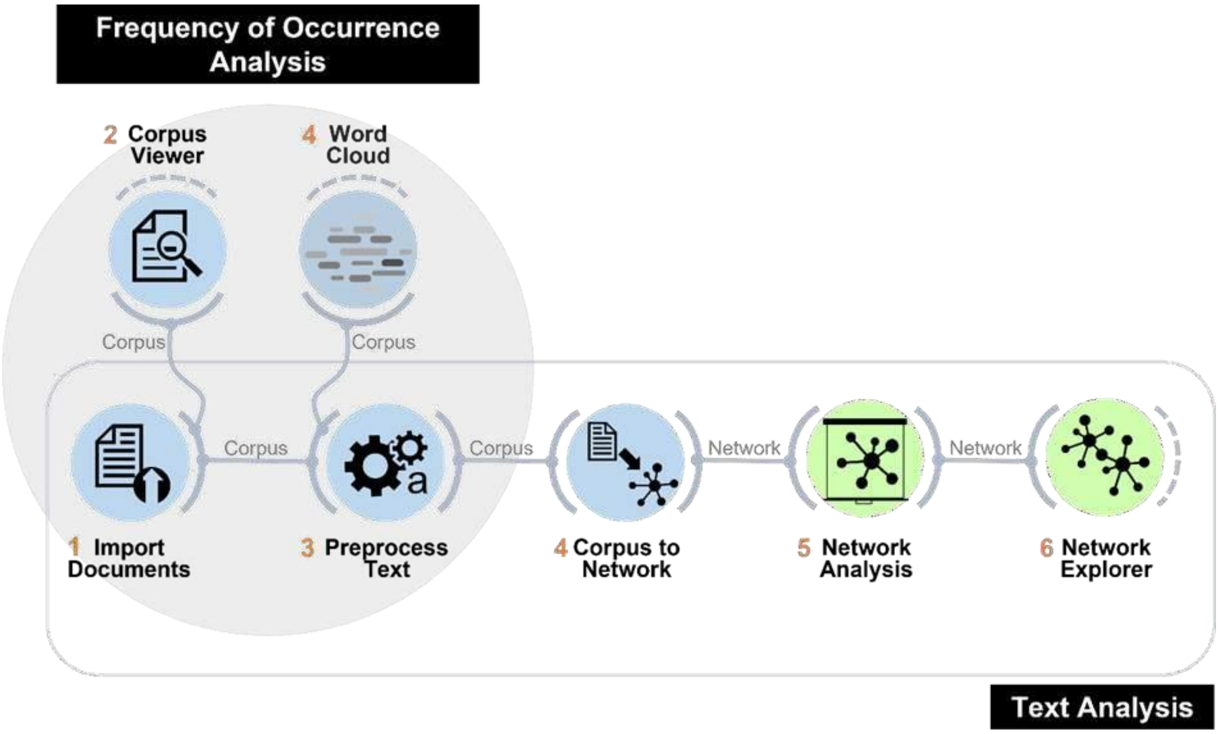

Figure 3: Text analysis widgets on Orange3 data mining (modified the original image of Orange 3, 2021)

Identifying frequency of occurrence of fashion codes

The big circle in Figure 3 demonstrates how the FO of the different fashion codes can be visualised. Documents are imported onto Orange3, pre-processed, and visualised through the word cloud. This widget's primary purpose is to display tokens in the corpus and denote the FO of a particular word in the corpus. Words are listed according to their FO (weight) in the widget.

Identifying the correlation between fashion codes

To identify the relationship between various codes, we must take further steps in processing our text data (squround in fig. 3). We separate our articles into single sentences through corpus to the network and then segment sentences into single words. After which, we transform these words into nodes (Ngrams). Our study set the frequency threshold to a minimum of 100 co-occurrences to control and leave out words unconnected to fashion.

Many unrelated words may still surface at this stage, and we can further control this by updating the stop word file. To quantify the relationship between design codes, our words are processed through Network analysis. This widget analyses key design features by measuring words with the highest DC to reveal the importance of that code compared to others through co-occurrence.

Findings

Frequency of occurrence of menswear design features

MW trends from fall 2012 to spring 2022 with the highest FO are shown in Table. 4. As anticipated, design elements associated with traditional MAS play dominant roles in MW. However, our results also show womenswear-related features to have emerged frequently with high FO suggesting fashion designers' attempts at subverting MAS. SMAS trends have seemingly eased themselves into mainstream MW collections materialising as keywords such as *soft, floral, and pink,* all with high FO.

Rank	Garment	*f*	Silhouette	*f*	Textiles	*f*	Patterns	*f*	Colour	*f*	Theme	*f*
1	Jacket	3,056	Tailored	453	Leather	1,202	Print	1,060	Black	1,319	Tailoring	
2	Shirt	1,912	Oversize	306	Denim	745	Check	451	White	937	Cl	
3	Pant	1,618	Loose	244	Felt	665	Stripe	407	Blue	6		
4	Suit	1,571	Cropped	185	Wool	589	Graphic	373	Green			
5	Coat	1,438	Volume	176	Cotton	588	Logo	337				
6	Knit	861	Relaxed	175	Silk	588	Jacquard					
7	Top	712	Slim	152	Nylon	426	Motif					
8	Sweater	694	Skinny	149	Cashmere	394	Em					
9	Jean	574	Tight	120	Velvet	3						
10	Outerwear	468	Elongated	119	Fur							
11	Bomber	448	Fitted	111	S							
12	Parka	423	Boxy									
13	Sportswear	376										
14	Sweatshirt	262										
15	Tee											
	m											

f = frequency/weight of word; m = mean value rounded to nearest digit

Table 4: Menswear design features

Correlation between fashion codes

SNA gender networks were generated for identifying correlations between design keywords (Table 5). DC values range from 0 (no centrality & importance) to 1 (central & of greatest importance). Low DC value features unconnected to the central network are listed at the bottom of the tables. Though unconnected to the main configuration, they are nevertheless important cyclical trends in MW. Codes with high DC values are dominant trends in MW.

Degree of Centrality (DC) values of design features (rounded to nearest digit)										
Garment	**DC**	**Silhouette**	**DC**	**Textiles**	**DC**	**Patterns**	**DC**	**Colour**	**DC**	**Theme**
Jacket	0.80	Tailored	0.12	Leather	0.40	Print	0.30	Black	0.40	Tailor
Shirt	0.60	Oversize/ Loose	0.10	Wool	0.30	Check	0.16	White	0.24	S
								Blue		
Pant	0.53			Silk	0.24	Stripe	0.12			
Coat/Suit	0.50			Denim	0.23	Jacquard /Gra				
Knit	0.30			Cotton						
Sweater	0.22			Nylon/Ca						
Top	0.18			Fine						
Bomber Jean/Parka Outerw	0.1									
Vest/Sweatshirt/Tee/Overcoat/Trench	0.10									
Features < 0.10: logo, trench, motif, orange, floral, cardigan, skinny, corduroy, brown, dye workwear, pajama, mesh, sportswear, washed, polo, fur, scarf, uniform, army, p vintage, formal, flannel, satin, painted, cropped, gold, khaki, relaxed, patchwork, baseball, volume, couture, blouson, masculine, tight, 80s, puffer, fitted, cape, jumpsuit, tank, cam animal, metallic, 70s, feminine, star, ha										
Outside network < 0.01: sep girly, performanc										

Table 5: Degree of centrality of design features

Analysis

Table 4 indicates garments to have the highest FO (m = 977) followed by textiles (m = 460), colour (m = 401), theme (m = 320), patterns (m = 315) and silhouette (m = 191). Keywords with the highest FO in each group include garment *jacket* (f = 3056), in silhouette *tailored* (f= 453), in textiles *leather* (f = 1,202), in patterns *print* (f = 1,060), in colour *black* (f = 1,319) and in theme *tailoring* (f = 826). Top ranking SMAS keywords include *tight* (f = 120), *floral* (f = 195), *heart* (f = 168), *animal* (f = 132), *pink* (f = 271), *yellow* (f = 223), *orange* (f = 204), *soft* (f = 374) and *couture* (f = 206). Though SMAS keywords scored high frequencies, traditional MAS features (Table 1) still dominate. All SMAS keywords have below mean values in each category apart from *soft* (f = 374) in theme group (m = 320) insinuating *soft* to play a fundamental role in MW collection themes.

Garments, textiles, and colours have also scored the highest centrality (table 5). The highest DC among garments, *jacket* scored DC = 0.80, in silhouettes *tailored DC* = 0.12, in textures *leather DC* = 0.40, in patterns *print DC* = 0.30, in colour *black DC* = 0.40 and in theme *tailoring*

DC = 0.21. SMAS related features *soft*, *yellow*, and *pink* are also seen with DC values at 0.12, 0.10 and 0.10, respectively. In addition, other SMAS trend keywords include *lace*, *floral*, *orange*, *satin*, animal, feminine, *tight* and *couture* at values < 0.10 and keywords *girly*, *pretty*, *romantic,* and *heart* at values < 0.01. Alike FO, our results show *soft*'s significance with the second highest DC among themes behind *tailoring* with *DC* = 0.21.bHowever, other SMAS keywords are not dominat trends in any way with the majority scoring *DC* = < 0.10.

Discussion

This study processed 3,047 fashion collection reports over 10 years to examine MW trends through SNA. The quantification of trend keywords through machine learning have assisted us in recognising MW trend patterns and examining how contemporary MW is interpreting *soft* style of Gen Z. Our results suggest garment, textile, and colour keywords to have the highest FO and DC values overall (table 6 & 7). Existing literature often discuss garments and colour as the most identifiable visual component that we can immediately recognise from a distance (Ellinwood, 2021). In table 4, various SMAS keywords appear with high FO in MW during fall 12 to spring 22. However, these trends do not subjugate traditional MAS dress styles that demonstrate male hegemony i.e., jacket (*f* = 3,056)/tailoring (*f* = 826). And in table 5, SMAS keywords again appear with DC values of over 0.10, with many between 0.01 and 0.10. Overall, though SMAS is a relatively new trend, we do see its weight in MW through FO & DC values. There is the implication that SMAS trends do play a vital role in the development of MW fashions; however, there is no indication suggesting a widespread shift to SMAS in MW.

Conclusion & limitation

This study demonstrates the feasibility of using machine learning in fashion forecasting, academic research, and companies' design directorial tools. We objectively identified developments in MW and examined how contemporary fashion interprets SMAS on the runway. Through probing the digital, we examine the complexities of fashion and MAS identity; how it is viewed and consumed in a broader scale. This study recognises the blurring of existing frontiers in fashion between the digital & tangible by sourcing data from online resources befitting our fast-paced digital era.

In academia, our paper delivers a systemical study of MW trends through semantic network analysis to identify and examine the correlation of fashion trends; in our case, SMAS trends were found. Our study illustrates how virtually formed Gen Z tribes have subverted MAS dress and disseminated into the physical by designers through the increasing normalization of SMAS trends in MW collections. We anticipate this study to instigate a new range of theories on dress & gender in fashion and prompts us to re-evaluate, re-interpret and update our preconvieved notions of MAS representation in fashion. With SMs' popularity and emphasis on individualism, future studies may wish to analyse how Gen Z use various virtual platforms/realities to perform their social identities and how it is translated into the tangible.

Abbreviations

CO = co-occurrences

DC = degree of centrality

FO = frequency of occurrence Gen Z = generation Z

MAS = masculinity/masculine MW = menswear

SM = social media SMAS = soft masculinity

SNA = semantic network analysis TMAS = toxic masculinity

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