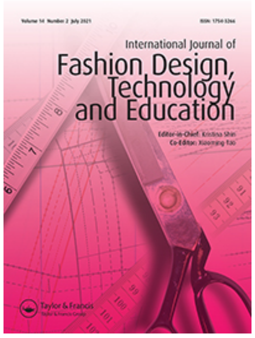

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Are fashion majors ready for the era of data science? A study on the fashion undergraduate curriculums in U.S. institutions

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ABSTRACT
As the fashion industry is becoming ever more data-driven, this study intends to understand whether the current fashion curriculums in U.S. education institutions have sufficiently introduced fashion majors to the topic of data science and prepared students for related skillsets. The results of MANOVA analysis based on course information collected from 45 fashion curriculums offered by leading U.S.-based fashion programmes show that: First, fashion programmes, in general, have incorporated some but very limited data science-related courses into the fashion curriculum. Second, school affiliation and programme type are two factors that have statistically significant impacts on fashion programmes' adoption of data science-related courses to the curriculum. Third, the current fashion curriculums are too rigid to allow more data science components without adding additional credit burdens. The findings call for a more balanced fashion curriculum to develop students' data science-related skillsets and suggest rethinking the future of fashion education in U.S. colleges.

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Fashion education; data science; fashion curriculum; business school

Introduction

As one of the most popular college majors among Generation Z (i.e. those born after 1995), over 50 undergraduate fashion programmes are currently offered by U.S.-based higher education institutions (Francis & Hoefel, 2018; Fashion Schools, 2020). These college programmes typically provide Bachelor of Science (BS) or Bachelor of Art (BA) degrees that concentrate on the design, making, or merchandising of fashion, apparel, and textile products (Palomo-Lovinski, Copeland, & Kim, 2019; Fashion Schools, 2020). Studies show that pursuing a career in the fashion industry after graduation is among the strongest motivations for students enrolled in an undergraduate fashion programme (Hodges & Karpova, 2009).

Meanwhile, due to the increasing availability of datasets of various kinds, from social media and consumer behaviour to market intelligence, more and more U.S. fashion companies leverage data science and related analytics tools to improve their business operations (Moore, 2019; Yu, Hui, & Choi, 2012). As the fashion industry is becoming ever more data-driven, the type of talents required by the industry and related skillsets needed are also quickly and fundamentally changing in nature (Agarwal, 2018). Notably, data science-related skills, i.e. the ability to understand, interpret, and analyze patterns, trends, and associations from data by using quantitative analysis tools, have become ever more relevant for future talents working in the fashion industry (Waller & Fawcett, 2013; Silva, Hassani, & Madsen, 2019).

While a few existing studies examined how effectively fashion programmes prepared students for traditional merchandising or design positions in the fashion industry, whether these programmes have prepared students ready for a data-intensive fashion industry remains mostly unknown (Hodges & Karpova, 2009; Lyu & Leslie, 2017; Ellington, Hahn, & McLeod, 2017). Thus, the purpose of this study is to investigate whether the current fashion curriculums in U.S. higher education institutions have sufficiently introduced students to the topic of data science and prepared for students' related competencies. Specifically, the study intends to focus on the following three research questions:

(1) Do the current undergraduate fashion programmes in U.S. higher education institutions incorporate data science-related courses into their curriculums?
(2) Do different types of undergraduate fashion programmes (such as design-focused versus merchandising-focused) in U.S. higher education institutions require data science-related courses similarly or differently?
(3) What are the primary challenges of incorporating more data science-related courses into the

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undergraduate fashion curriculums in U.S. higher education institutions?

This study is of both significant academic and application values:

First, the findings of the study will fulfill a critical research gap. Existing studies only evaluated the status and effectiveness of how conventional topics related to the fashion industry, such as retailing and merchandising skills, have been integrated into the fashion curriculums (Ellington et al., 2017; Wang & Ha-Brookshire, 2018; and Palomo-Lovinski et al., 2019). Instead, this study will create new knowledge about how U.S.-based undergraduate programmes have exposed fashion majors to data science as a non-traditional topic for fashion students but growing in importance to students' future career success.

Second, the study's findings will provide valuable inputs for U.S. higher education institutions to continuously improve and update their fashion curriculums and make them most relevant in the twenty-first century. More specifically, the findings of the study can serve as a benchmark to help fashion programmes better understand the opportunities, challenges, and strategies for developing data-science related components in their curriculums.

Related, the findings of the study will also benefit hundreds of thousands of college students pursuing or planning to pursue a fashion major. Particularly, the results will help raise students' awareness of the changing nature of fashion and remind them of the importance of improving the knowledge and skillsets needed in the data-driven fashion industry (Silva et al., 2019).

The rest of the paper will include four sections. First, we will provide a thorough literature review of the application of data science in the fashion industry and the state of undergraduate fashion education in U.S. higher education institutions. This section will also introduce the theoretical framework that shapes the design of the study. Next, we will discuss the data source of the study and the research methods. Then, we will present the data analysis results. In the last section, we will discuss the implications of the findings and the future research agenda.

Literature review

Application of data science in the fashion industry

With the increasing availability of data inputs of various kinds, from sales, social media to consumers' online shopping behaviours and the advancement of related data analysis tools, more and more fashion companies are leveraging data science and related business analytics tool in support of their daily business operations (Vicario & Coleman, 2019; Silva et al., 2019). The usage of data science in the business aspect of fashion has been particularly popular, such as supply chain management, inventory control, sales forecasting, and analysing consumers' purchasing behaviours (Jain, Bruniaux, Zeng, & Bruniaux, 2017; Acharya, Singh, Pereira, & Singh, 2018; Silva et al., 2019). For example, studies show that fashion companies have benefited from mass customisation, i.e. making customised and personalised items on a large scale, by leveraging data science (Tiihonen & Felfernig, 2017). Through analysing data inputs of consumers' purchasing history and demographics, data science-based mass customisation allows fashion companies to more effectively cater to consumers' preferred style, fit, and colour and meet their evolving demands (Tiihonen & Felfernig, 2017). Likewise, Landmark and Sjøbakk (2017) demonstrated the effectiveness of using data inputs collected from the Radio Frequency Identification (RFID) tag in helping fashion brands optimise inventory levels and avoid overstock.

In addition to business aspects, fashion companies are also leveraging data science to improve or fundamentally change how they create new products (Giusti & Alberti, 2018). For example, some fashion companies have begun to integrate data analytics and machine learning in their apparel design process (Varshney et al., 2019). By comparing the fashion trends forecasts generated by WGSN and EDITED, Dubreuil and Lu (2020) found that big-data tools have great potential to forecast fashion trends, particularly in the area of colour and patterns. Further, some well-known fashion icons, such as Gap Inc., have attempted to remove the 'creative director' position and instead use data scientists to design new products (Israeli & Avery, 2017).

Further, the combination of data science and fashion has attracted many new players, especially technology companies, to enter the fashion business. These tech newcomers, such as EDITED, Trendalytics, and Style Sage, provide big-data based analytics tools that help conventional fashion brands and retailers more powerfully and effectively analyze their sales, identify market-popular styles, trends, textile materials, and design product assortment and pricing strategies for their target consumers (Dubreuil & Lu, 2020).

Fashion jobs and data science-related skills

Not only the increasing usage of data science changes how fashion brands and apparel retailers design, merchandise, market, and deliver their products, but also it affects companies' demand and skillsets expectations for talents.

On the one hand, fashion companies' growing use of data science creates new types of jobs that did not exist in the past. For example, an analysis of job openings by U.S. fashion brands and retailers posted on the Business of Fashion (BOF) from January 2019 to July 2020 shows that job titles such as 'data editor', 'data scientists', and 'smart inventory manager' were among the most in-demand (Business of Fashion, 2020). Notably, the job advertisements for these positions often explicitly require the applicants to acquire a solid knowledge of data science, such as 'experience with Household Data, POS Data, Panel Data, customer analytics, web analytics', 'experience with large volumes of sparse categorical data, linear models and machine learning', and 'proven experience in areas of optimization, statistics, machine learning, and inventory theory' (Business of Fashion, 2020). The qualified applicants also need to demonstrate the ability to analyze and interpret fashion-related datasets using statistical, analytical, or data mining tools, such as 'working with data and interpreting numbers', 'apply concepts of profitability and statistical inference to practical situations', and 'communicate findings and data science concepts clearly to both technical and non-technical audiences' (Milner, 2020; Business of Fashion, 2020).

A survey of nearly 25 executives from leading U.S.-based fashion companies also suggests that 'data scientists' are among the top five positions these fashion companies are most likely to increase hiring through 2025 (Lu, 2020).

Meanwhile, with the widespread usage of data science in almost all aspects of a fashion company's business operations, even the expectation for traditional 'merchandising' and 'design' positions are gradually adding data-related new requirements. For example, based on in-depth interviews of industry professionals, Zhong and Mitra (2020) found that conducting a statistical analysis of sales data and demand forecasting has become an integral part of fashion buyers' essential job responsibilities today. Likewise, through semi-structured interviews with in-house design teams, Payne (2016) suggests that fast fashion retailers have been increasingly expecting their designers to use business analytics tools and consult quantitative data inputs in the design process. According to some job post websites, analysing and interpreting data inputs is more often listed as a job responsibility for entry-level positions in fashion merchandising and design areas (Business of Fashion, 2020).

Studies further suggest that data science-related skillsets expected for talents working in the fashion industry typically include three aspects (see Figure 1):

(1) *Basic math and statistics knowledge*. Big data relies heavily on mathematics and statistics tools (Moore, 2019). Understandably, future talents working in the data-driven fashion industry are highly expected to obtain solid math and statistics knowledge (Silva et al., 2019). Based on a descriptive analysis of the standard test scores of over 200 students enrolled in 13 U.S.-based fashion merchandising programmes, Miles (2016) also contends that fashion curriculums should strengthen students' proficiency in mathematics as working in the fashion industry today means 'playing with numbers' routinely.
(2) *Quantitative reasoning skills*. Quantitative reasoning skills refer to analysing and interpreting quantitative data and using them as inputs in decision-making (Elrod, 2014). Today, fashion companies increasingly rely on data analysis results to make business decisions, from planning merchandise, managing inventory to the creation of new products (Azevedo & Carvalho, 2012). Thus, the ability to read, understand, and interpret numerical data output in the fashion industry context becomes key for the workforce (Johnson, 2012).
(3) *Data software skills*. Knowing how to use data processing and analysis software is also part of the skillsets required for fashion majors (Waller & Fawcett, 2013). For example, Wang and Ha-Brookshire (2018) found that fashion employers identified Excel as a must-know tool for fashion students, given the wide usage of the software by fashion companies today. As brands and retailers are building a more digital-based business model, the demand for software skills and digital competency could broaden in scope further to areas such as business analysis, coding, and data mining (Kalbaska & Cantoni, 2017, april; Bremner, 2017).

Undergraduate fashion curriculums in U.S. higher education institutions

Fashion remains one of the most popular college majors among Generation Z, the main body of U.S. college students today (Francis & Hoefel, 2018). As of June 2020, over fifty U.S. higher education institutions offer dedicated undergraduate fashion programmes (Fashion Schools, 2020). In general, these fashion programmes

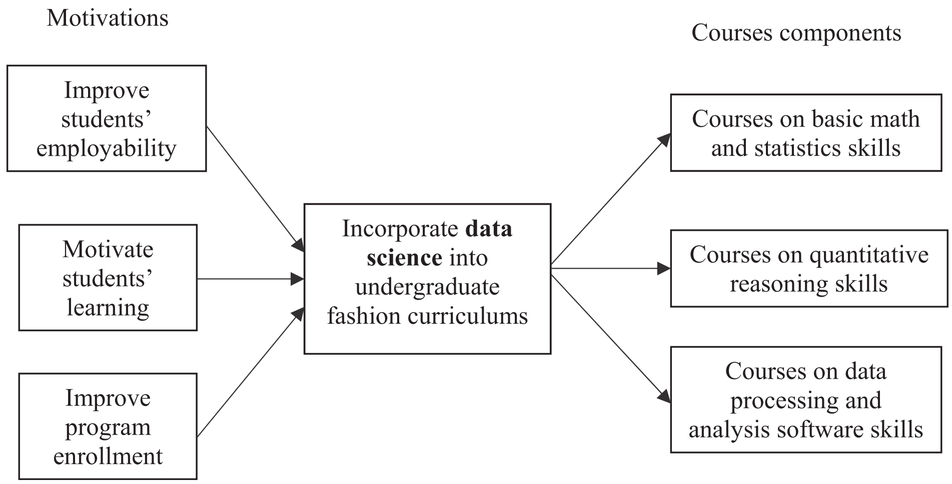

Figure 1. Data Science in Fashion Curriculums: A Theoretical Framework.

allow students to focus their studies either on the business aspect of fashion (i.e. with a concentration on merchandising, management, or marketing), the creative side (i.e. with a concentration on apparel design or product development), or both (Ha-Brookshire & Labat, 2015).

On the other hand, as a result of academic units reorganisation over the past decades, undergraduate fashion programmes in U.S. higher education institutions currently are using a great variety of names, such as 'Fashion and apparel studies', 'Apparel, merchandising and design', 'Consumer, apparel and retail studies', and 'Textile and apparel management'(Fashion Schools, 2020). These fashion programmes are also affiliated with different colleges, ranging from human sciences, design schools, arts & sciences to business (Ha-Brookshire & Labat, 2015). Notably, the difference in college affiliation reflects the 'identity' of respective fashion programmes and affects the particular academic resources accessible to them (Radclyffe-Thomas, 2018). For example, fashion programmes housed under the college of business, in general, arrange their students to take more business-related courses, whereas programmes under design schools can offer more specialised apparel design courses based on faculty's expertise (Ha-Brookshire & Labat, 2015; Radclyffe-Thomas, 2018).

A review of undergraduate fashion curriculums in U.S. higher education institutions suggests three distinct features:

First, fashion curriculums across U.S. higher education institutions overall share some standard core requirements. For example, fashion programmes typically require their majors to take courses that address apparel production, fashion trend analysis, and design. Meanwhile, fashion programmes also assign different specialised courses for merchandising majors and design majors. For example, most merchandising-oriented fashion curriculums include required courses such as retail buying, merchandising, branding, and marketing. In comparison, fashion design students usually are required to take draping, pattern making, and computer-aided design (CAD) courses (Pasricha & Kadolph, 2009; Ha-Brookshire & Labat, 2015)

Second, fashion curriculums in U.S. higher education institutions, in general, are application-oriented. Some fashion design schools, in particular, focus on improving students' hands-on experiences in the learning process (Pasricha & Kadolph, 2009). Studies also show that most American students that choose to pursue an education in fashion would like to specifically select the fashion industry as their future career path (Hodges & Karpova, 2009). Thus, fashion programmes in U.S. higher education institutions have a unique responsibility to prepare for students' employability and their thriving long-term career success in the fashion industry (Hodges & Karpova, 2009).

Third, most fashion programmes in U.S. higher education institutions regularly review, revise, and update their curriculums to keep up with the fashion industry's changing nature (Pasricha & Kadolph, 2009). For example, in recent years, more and more fashion programmes have launched dedicated courses to enhance students' knowledge and awareness of sustainability, given its growing importance to fashion companies (Agarwal, 2018; Palomo-Lovinski et al., 2019). As fashion brands and retailers increasingly favour job applicants with previous working experiences, fashion programmes in U.S. higher education institutions also start to require an internship experience before students' graduation.

Incorporating data science into fashion curriculums: A theoretical framework

In summary, numerous studies have evaluated the effectiveness of undergraduate fashion curriculums in preparing students' knowledge, skills, and competencies for convention fashion merchandising, marketing, and design positions (Pasricha & Kadolph, 2009; Ha-Brookshire & Labat, 2015; Lyu & Leslie, 2017; Marniati & Witcjaksono, 2020). Existing studies have also unanimously suggested the growing importance of data science to the fashion industry and how data science has been substantially changing the nature of fashion jobs and related skillets for the workforce (Azevedo & Carvalho, 2012; Luce, 2018; Acharya et al., 2018; Dubreuil & Lu, 2020). However, whether the current fashion curriculums in U.S. higher education institutions have sufficiently introduced students to the topic of data science and improved students' related competencies remain mostly unknown.

As illustrated in Figure 1, theoretically, incorporating data science into fashion curriculums could be motivated by three primary benefits: First, encourage students to learn. Studies show that when students see the connection between the content of their classroom learning and their future work in the industry, it will positively impact students' learning motivations (Cheng, 2018). Second, improve students' employability. When college education matches the industry demands in terms of students' knowledge and skillsets, graduates are more likely to be hired and achieve long-term career success (Bremner, 2017). Exposing undergraduates of fashion majors to data science in the curriculums can help prepare students ready for the data-driven fashion industry. Third, with industry-relevant college experience and graduates' successful job placement, incorporating data science into the fashion curriculums can further benefit fashion programmes' enrollment (Hodges & Karpova, 2009).

On the other hand, given the application of data science in the fashion industry and the expected skillets for the future workforce, as illustrated in Figure 1, data science-related courses in undergraduate fashion curriculums could include three major components: 1) basic math and statistics knowledge; 2) quantitative reasoning skills; 3) software skills (Waller & Fawcett, 2013; Kalbaska & Cantoni, 2017, april; Bremner, 2017).

Research Method

Data collection

For the study, between June and August 2020, we collected the detailed undergraduate fashion curriculum sheets from 4-year higher education institutions on the list of the *2020 top 50 U.S. fashion programmes* ranked by Fashion Schools, one of the most comprehensive and authentic rankings of its kind (Fashion Schools, 2020). Then, we conducted a content analysis of the curriculum sheets downloaded from these institutions' websites. Based on interpreting the course title and the course description, the content analysis intends to understand the top 50 fashion programmes' detailed course offerings by major course categories (Schreier, 2012). Specifically, to evaluate the extent to which the examined fashion programmes have exposed students to the subject of data science and prepared students for related skillsets, we coded the curriculum sheets based on the following scheme:

- *Business:* if the fashion programme is under business school = 1; otherwise = 0. We look at the factor of school affiliation in the study because those fashion programmes under the business school may have more access to data science-related academic resources than otherwise (West, 2018). As many business schools participate in accreditation programmes, whether a fashion programme is affiliated with business schools may also affect its overall course offerings and the structure of degree-required courses for its fashion majors (Clayton & Clopton, 2019).
- *Programme type*: if the programme is merchandising-focused = 1 (i.e. the programme name or programme description explicitly mentions words or phrases such as marketing, merchandising, management, or business aspect of fashion). If the programme is apparel design-focused = 0 (i.e. the programme name or programme description explicitly mentions words or phrases such as art, design, product development, or creative aspect of fashion). A merchandising and design dual programme = 2 (i.e. when the programme adopts a relatively balanced curriculum that emphasizes both fashion merchandising and design). It is necessary to compare merchandising and design-oriented fashion curriculums as different types of programmes commonly ask students to take respective specialised courses (Ha-Brookshire & Labat, 2015; Ellington et al., 2017). Given the difference in course offerings, it is also likely that programme type may be a significant factor that affects how data science-related courses have been incorporated into the fashion curriculums.
- *Math & Stat courses:* refer to math and statistics courses as a percentage of the fashion major's total credit requirements. Courses in this category shall explicitly mention words such as 'math', 'statistics',

'algebra', and 'calculus' in their course title (Schofield, 2012).

- *Data courses:* refer to those courses that focus on data science or data analysis as a percentage of the fashion major's total credit requirements. Courses in this category need to explicitly mention the word 'data' or 'data analysis' in their title or the course description (Baumer, 2015).
- *Quantitative merchandising courses:* refer to those merchandising courses that intend to improve students' quantitative analysis skills as a percentage of the fashion major's total credit requirements. Courses in this category need to address a particular fashion merchandising topic (such as assortment planning) and aim to improve students' quantitative reasoning skills based on their course description (Yu, 2018).
- *Non-quantitative merchandising courses:* refer to non-quantitative merchandising courses as a percentage of the fashion major's total credit requirements. Courses in this category need to address a particular fashion merchandising topic (such as branding); however, based on the course description, these courses do not include a learning component or learning goal that intends to improve students' quantitative reasoning skills.
- *Design courses*: refer to fashion or apparel design courses as a percentage of the fashion major's total credit requirements. Courses in this category need to address particular apparel or fashion design topics (such as draping and pattern making) based on the course title or description (Grose, 2017)
- *Free electives*: refer to free elective courses as a percentage of the total credit requirements for the fashion major.

As illustrated in Figure 1, analysing the credit requirement for *Math & Stat courses*, *Data courses*, and *Quantitative merchandising courses* can reveal whether current fashion curriculums in these top 50 U.S.-based fashion programmes have sufficiently introduced students to data science and provided ample opportunities to improve students' related competencies. On the other hand, understanding the credit requirement for *Non-quantitative merchandising courses, Design courses,* and *Free electives* can help identify the additional opportunities and challenges of incorporating data science into the fashion curriculums.

Data analysis

Given the research objective and nature of the data collected, we adopted the multivariate analysis of variance (MANOVA) technique for the data analysis. MANOVA is commonly used to compare the mean value of observation vectors to see whether they are sufficiently different between groups (Huberty & Olejnik, 2006). MANOVA also has the advantage of dealing with multiple dependent variables in the model without inflating Type I errors (Lu, 2012).

In this study, MANOVA can help us compare the structure of fashion curriculums, particularly the requirement for data-science related courses, among fashion programmes with different school affiliations and programme types. Specifically, we use six dependent variables that measure the course structure of the fashion curriculum, i.e. *Math & Stat courses, Data courses, and Quantitative merchandising courses, Design courses, Non-quantitative merchandising courses, and Free electives*. Meanwhile, we use the *Business* and *Programme type* as the independent variables, which theoretically are suggested to impact the incorporation of data science-related courses in the fashion curriculums (Ellington et al., 2017; Clayton & Clopton, 2019).

Results and Discussion

Descriptive analysis

Altogether, 45 fashion curriculums from the top 50 fashion programmes that provide the complete course information needed for this study were included in the analysis. Reflecting on the history of the fashion academic discipline (Ha-Brookshire & Labat, 2015), the vast majority (N=42) of these fashion curriculums are offered by programmes housed under colleges such as Human Sciences, Arts and Sciences, and School of Design (i.e. *Business = 0).* In contrast, much fewer fashion programmes have joined the business school (i.e. *Business* = 1). Meanwhile, these fashion curriculums have a balanced representation of different types of fashion programmes, including 14 design-oriented (i.e. *Programme type* = 0), 17 merchandising-oriented (i.e. *Programme type* = 1), and 14 dual programmes (i.e. *Programme type* = 2). As summarised in Tables 1–3:

First, the results show that fashion programmes in U.S. higher education institutions have incorporated

Table 1. Summary of fashion curriculums.

Variables	Mean Value ($N = 45$)
Math & Stat courses	4.1%
Data courses	0.8%
Quantitative merchandising courses	5.2%
Data science related courses subtotal	10.1%
Non-quantitative merchandising courses	25.0%
Design courses	13.4%
Free electives	7.9%

Table 2. Summary of fashion curriculums by college affiliation.

Mean of variables	*Business* = 0 (*N* = 42)	*Business* = 1 (*N* = 3)
Math & Stat courses	4.1%	4.5%
Data courses	0.6%	3.1%
Quantitative merchandising courses	5.0%	8.4%
Data science related courses subtotal	9.7%	16.0%
Non-quantitative merchandising courses	25.6%	16.7%
Design courses	13.6	11.1%
Free electives	7.6%	11.6%

some but limited data-science related courses into their curriculums. Specifically, as shown in Table 1, data science-related courses, on average, accounted for around 10.1% of the total degree required credits in the fashion curriculums in U.S. higher education institutions. However, the detailed requirement for different types of data-science related courses varies significantly. For example, often included as a component of the general education requirement, fashion curriculums, on average, assign 4.1% of their total required credits for *Math & Stat* (i.e. mathematics and statistics courses). Likewise, fashion programmes in U.S. higher education institutions, on average, set 5.2% of their total required credits for *Quantitative merchandising* (i.e. merchandising courses that intend to improve students' quantitative analysis skills). In comparison, *Data courses* (i.e. those courses that focus on data science or data analysis) typically make up less than 1% of the total credits taken by a student enrolled in a U.S.-based fashion programme.

Second, college affiliation and program type seem to impact the extent to which data science courses have been incorporated into the fashion curriculums. Specifically, as shown in Table 2, regarding the percentage of data science-related courses required, there is a notable discrepancy between a fashion programme affiliated with the business school (16.0% for *Business* = 1) and otherwise (9.7% for *Business* = 0). Further, as shown in Table 3, data-science-related courses' requirement seems to be significantly different between design and merchanding-oriented fashion programmes.

Table 3. Summary of fashion curriculums by programme type.

Mean of variables	Programme type = 0 (*N* = 14)	Programme type = 1 (*N*=17)	Programme type = 2 (*N* = 14)
Math & Stat courses	4.1%	3.9%	4.4%
Data courses	0.3%	0.8%	1.2%
Quantitative merchandising courses	1.1%	7.7%	6.3%
Data science related courses subtotal	5.5%	12.4%	11.9%
Non-quantitative merchandising	13.4%	36.5%	22.8%
Design courses	29.8%	5.9%	6.1%
Free electives	6.1%	7.6%	10.1%

Third, traditional merchandising and design courses still account for the lion's share in the fashion curriculums. For example, *Non-quantitative merchandising courses* (i.e. courses that address a particular fashion merchandising topic but do not include a learning goal to improve students' quantitative reasoning skills) make up as high as 25% of the total credits required across fashion programmes in U.S. institutions. Likewise, design courses make up 13.4% of the total credits required regardless of programme type or college affiliations. This result suggests that most fashion programmes in U.S. higher education institutions still expect students to take a substantial amount of courses that address traditional topics specific to the fashion academic discipline (Robeck & Pattison, 2013; Lyu & Leslie, 2017).

Fourth, most fashion curriculums in U.S. higher education institutions leave limited free elective courses for students. As shown in Table 1, on average, free electives account for less than 8% of the total credits in fashion programmes offered by U.S. higher education institutions, or roughly only 2–3 courses in total. The results also show that fashion programmes under the business school (i.e. *Business = 1*) overall are more lenient in allowing fashion majors to take free electives than otherwise (i.e. *Business = 0*).

MANOVA analysis

As the credits requirements for data-science related courses appear to be different across fashion programmes under different college affiliations (i.e. variable *Business*) and programme type (i.e. variable *Programme type*), we further conduct the multivariate analysis of variance (MANOVA) to evaluate whether such difference is statistically significant (Huberty & Olejnik, 2006).

MANOVA assumption test

The Box's test of equality of covariance was first conducted to ensure the data of the study meets the equality of covariance assumption and is appropriate for the MANOVA analysis (Denis, 2018). The results show that Box's M value exceeds 82.16 (*P-value>0.05)*. This means that at the 95% confidence level, we cannot reject the null hypothesis that the within-group covariance is equal, i.e. the data of the study meets the MANOVA equality of covariance assumption requirement.

Main effect test

The MANOVA main effect test is conducted to evaluate whether college affiliations (i.e. variable *Business*) and

Table 4 Results of the MANOVA main effect test.

Statistics/Variables	Business	Programme type
Pillai's trace	0.381 (0.008)**	0.949 (0.000)**
Wilks' lambda	0.619 (0.008)**	0.265 (0.000)**
Hotelling-Lawly trace	0.616 (0.008)**	1.966 (0.000)**
Roy's greatest root	0.616 (0.008)**	1.379 (0.000)**

Note: Number in the bracket is *p*-value; $^{*}p < 0.05$, $^{**}p < 0.01$.

programme type (i.e. variable *Programme type*) overall have an impact on the course structure of fashion curriculums in U.S. higher education institutions (Denis, 2018). As shown in Table 4, the Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root tests all indicate that the main effect was statistically significant at the 95% confidence level (*P*-value<0.05). This result echoes the numbers in Tables 2 and 3, suggesting that whether a fashion programme is under the business school and whether it is design or merchandising-oriented has a statistically significant impact on the structure of the fashion curriculums and the specific type of courses students are required to take.

Between-subject test

The between-subject test was further conducted to explore which of the six dependent variables that measured the course structure of fashion curriculums substantially contributed to the statistically significant MANOVA main effect (Denis, 2018). As shown in Table 5:

First, the F-test results reject the null hypothesis that the values of *Data courses* and *Quantitative merchandising courses* are equal at the 95% confidence level for fashion programmes with different college affiliation in U.S. higher education institutions (*P*-value<0.05). As shown in Table 2, thanks to more availability of related academic and faculty resources, fashion programmes under business school (i.e. *Business* = *1*), on average, ask their students to take more *Data courses* and *Quantitative merchandising courses* those that are not (i.e. *Business* = *0*). The between-subject test confirms that such a difference in course requirement is statistically significant.

Table 5. Results of between-subject test F-value.

Variables	Business	Programme type
Math & Stat courses	0.248 (0.622)	0.054 (0.947)
Data courses	8.34 (0.006)**	12.56 (0.000)**
Quantitative merchandising courses	5.74 (0.022)*	15.698 (0.000)**
Traditional design courses	0.267 (0.608)	5.823 (0.006)*
Non-quantitative merchandising courses	2.32 (0.136)	3.105 (0.056)
Free electives	0.872 (0.356)	1.088 (0.347)

Note: Number in the bracket is *p*-value; $^{*}p < 0.05$, $^{**}p < 0.01$.

Second, the F-test results also reject the null hypothesis that the values of *Data courses, Quantitative merchandising courses*, and *Traditional design courses* are equal at the 95% confidence level among fashion programmes of different types in U.S. higher education institutions (*P*-value<0.05). As shown in Table 3, merchandising programmes (*Programme type* = *1)* and dual programmes *(Programme type* = *2*), on average, ask their students to take more *Data courses* and *Quantitative merchandising courses* than design-oriented fashion programmes (*Programme type* = *0).* Meanwhile, design-oriented fashion programmes (*Programme type* = *0)*, not surprisingly, place more emphasis on *Traditional design courses* as suggested by previous studies also (Ellington et al., 2017). The between-subject test confirmed that such a difference in course requirement is statistically significant.

Third, based on the results of the F-test, at the 95% confidence level, we cannot reject the null hypothesis that the credits requirements for *Math & Stat courses*, *Non-quantitative merchandising courses,* and *Free electives* are different among fashion programmes with different college affiliation or in different programme type in U.S. higher education institutions (*P-value*>0.05). In other words, the results suggest that fashion programmes in U.S. higher education institutions statistically have similar requirements for these three particular course categories regardless of these programmes' college affiliation (i.e. variable *Business*) and types (i.e. variable *Programme type*).

Contrast analysis

The between-subject test suggested that design-oriented (*Programme type* = *0)*, merchandising-oriented (*Programme type* = *1*), or dual fashion programmes (*Programme type* = *2*) in U.S. higher education institutions place different requirements for *Data courses, Quantitative merchandising courses*, and *Traditional design courses.* As the third step of the MANOVA procedure, we conducted a contrast analysis to explore whether these various types of fashion programmes *each* have their unique requirement for *Data courses, Quantitative merchandising courses*, and *Traditional design courses* statistically (Huberty & Olejnik, 2006). As shown in Table 6:

Table 6. Results of contrast analysis.

Variables	Design vs. Merchandising programmes	Design vs. Dual programmes	Merchandising vs. Dual programmes
Data courses	0.005 (0.426)	0.006 (0.035)**	0.005 (0.431)
Quantitative merchandising courses	0.009 (0.000)**	0.010 (0.000)**	0.009 (0.120)
Traditional design courses	0.036 (0.000)**	0.038 (0.000)**	0.036 (0.945)

Note: Number in the bracket is *P-value*; $*p < 0.05$, $**p < 0.01$.

First, for *Data courses*, design-oriented fashion programmes (*Programme type=0*) and dual programmes (*Programme type = 2*) are suggested to have a different requirement at the 95% confidence level (*P-value<0.05*). Meanwhile, no clear evidence indicates that the requirement between merchandising-oriented programmes (*Programme type = 1*) and dual programmes (*Programme type = 2*) are statistically significant.

Second, for *Quantitative merchandising courses,* design-oriented fashion programmes (*Programme type=0*) are suggested to have a different requirement from both merchandising-oriented programmes (*Programme type = 1*) and dual programmes (*Programme type = 2*) at the 95% confidence level (*P-value<0.05*). Meanwhile, no clear evidence suggests that the requirement for *Quantitative merchandising courses* are statistically significant between merchandising-oriented fashion programmes (*Programme type = 1*) and dual programmes (*Programme type = 2*).

Third, for *Traditional design courses,* design-oriented fashion programmes (*Programme type=0*) are suggested to have a different requirement from both merchandising-oriented programmes (*Programme type = 1*) and dual programmes (*Programme type = 2*) at the 95% confidence level (*P-value<0.05*). Meanwhile, no clear evidence suggests that the requirement for *Traditional design courses* are statistically significant between merchandising-oriented programmes (*Programme type = 1*) and dual programmes (*Programme type = 2*).

Together with the figures in Table 3, the results suggest that design-oriented fashion programmes in U.S. higher education institutions are remarkably short of *Data courses* and *Quantitative merchandising courses* – two critical components of data science education in the curriculum. In comparison, merchandising-oriented programmes and dual programmes are relatively better positioned to leverage *Quantitative merchandising courses* required in the curriculum to expose students to data science and improve students' related skillsets.

Conclusions and implications

Conclusions

As the fashion industry is becoming ever more data-driven, this study intends to understand whether the current fashion curriculums in U.S. higher education institutions have sufficiently exp fashion majors to the topic of data science and prepared students for related skillsets. The results of MANOVA analysis based on course information collected from 45 fashion curriculums offered by programmes on the list of *2020 top 50 U.S. fashion programmes* ranked by Fashion Schools (2020) show that:

First, fashion programmes in U.S. higher education institutions, in general, have incorporated some but very limited data science-related courses into the fashion curriculum. Fashion students have the chance to prepare for their data-science-related skillsets, mostly through mathematics and statistics courses and merchandising courses that require some quantitative data analysis components. However, courses that directly address data science or data analysis remain rarely seen in the fashion curriculum.

Second, the MANOVA analysis suggests that school affiliation and programme type are two factors that have statistically significant impacts on fashion programmes' adoption of data science-related courses to the curriculum. Specifically, the results of the MANOVA between-subject test suggest that U.S. fashion programmes currently under business schools require relatively more data science-related courses than otherwise. Meanwhile, statistically, fashion programmes that are merchandising-oriented or focus on both fashion merchandising and design (i.e. dual programmes) require students to take relatively more data science-related courses than those programmes that are design-focused only.

Third, the results further show that traditional design courses and non-quantitative merchandising courses together, on average, account for nearly 40% of a fashion programme's total credit requirements compared with only 8% for free electives (i.e. two to three 3-credit courses in total). Such a rigid curriculum structure makes it challenging to strengthen fashion students' data-science without adding additional credit burdens.

Implications

The study's findings created new knowledge about the state of data science education and related skillsets preparation of fashion majors in U.S. higher education institutions. The results of the study also have several important implications:

First, the study results suggest a need for greater exposure to data science-related content in U.S. higher education institutions' fashion curriculums. While many fashion students and faculty see fashion education about creativity and artistic skills, with the increasing usage of data by fashion companies, maybe it is time to change the mindset and treat data science also as an essential component of the twenty-first-century fashion curriculum (Ogle, Hyllegard, Rambo-Hernandez, & Park, 2017; Luce, 2018). Particularly, those design-oriented fashion programmes need to shift the culture of avoiding 'math and numbers' and instead create more opportunities for their students to play with data and improve students' quantitative reasoning skills (Pasricha & Kadolph, 2009; Dubreuil & Lu, 2020).

Second, the findings suggest that fashion programmes in U.S. higher education institutions could consider offering a more balanced course structure to comprehensively develop students' data science-related skillsets. Notably, as illustrated in the findings, most data science-related courses in current fashion curriculums are limited to *Math & statistics courses* and *Quantitative merchandising courses*. While these courses help prepare students' competencies in basic math and quantitative reasoning skills, they may not directly improve students' data processing and data analysis software skills, which are also regarded as essential for the future workforce in the fashion industry (Waller & Fawcett, 2013; Kalbaska & Cantoni, 2017, april; Bremner, 2017). As the available learning resources are limited, fashion educational programmes may consider building strategic industry partnerships to help develop related learning material and access the state of the art data analysis tools widely used by fashion companies.

Further, the findings imply a new opportunity for rethinking or even reforming fashion education in U.S.-based colleges. Even though the fashion industry and the fashion job market have substantially changed (Moore, 2019; Lu, 2020), as the study found, traditional fashion courses still account for nearly half of the fashion curriculum's credit requirements in most U.S. higher education institutions. Fashion programmes may consider providing fashion majors with more flexibilities in the curriculum to explore emerging topics that are growing in importance to students' employability in the fashion industry but beyond the coverage of traditional fashion courses, such as data science (Business of Fashion, 2020). Educational institutions may also consider launching new interdisciplinary fashion programmes that target fast-growing but non-traditional jobs in the fashion industry, such as fashion data scientists (Daugherty, Wilson, & Michelman, 2019). These new fashion programmes may further appeal to students interested in the science, technology, engineering, and mathematics (STEM) discipline, resulting in an expanded and more diverse student body of fashion majors.

Future research agendas

Despite the interesting results, this study also has several limitations that future research might overcome.

First, while this study focused on analysing the curriculum sheets and the course description, it would be beneficial to conduct in-depth interviews with fashion educators to identify the best approaches to incorporate data science into the fashion curriculum. The interviews can provide a valuable context that helps understand the resources required, the philosophy behind the design of a twenty-first-century fashion curriculum with a data science component, and other opportunities and challenges of strengthening data science education among fashion majors.

Second, while this study examined U.S.-based fashion programmes only, it could be interesting to explore how fashion programmes in other parts of the world, such as Europe and Asia, have incorporated data science into their fashion curriculums. Comparing the differences and similarities of fashion curriculums across different countries can reveal the impact of data science on shaping the global fashion industry's big landscape and inspire new thinking on the future of fashion education (Richardson, 2019).

Future studies can also use case studies or survey methods to evaluate the 'return of investment' of improving fashion students' data science-related competencies on their employability in the job market. The results can provide additional inputs illustrating the impact of data science on the fashion job market and providing valuable inputs guiding fashion programmes to strengthen their students' data science-related competencies most effectively.

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References

Acharya, A., Singh, S. K., Pereira, V., & Singh, P. (2018). Big data, knowledge co-creation and decision making in fashion industry. *International Journal of Information Management*, *42*, 90–101.

Agarwal, V. (2018). Sustainable fashion education in changing world scenario. *European Journal of Sustainable Development*, *7*(1), 365-373.

Azevedo, S. G., & Carvalho, H. (2012). Contribution of RFID technology to better management of fashion supply chains. *International Journal of Retail & Distribution Management*, *40*(2), 128–156. doi:10.1108/09590551211201874

Baumer, B. (2015). A data science course for undergraduates: Thinking with data. *The American Statistician*, *69*(4), 334–342.

Bremner, P. A. M. (2017, June 6). *From fourth year to the outside world: are we making our fashion graduates 'work ready' - are their skills transferable into the workplace?* OpenAIR@RGU Home. https://rgu-repository.worktribe.com/output/246767/from-fourth-year-to-the-outside-world-are-we-making-our-fashion-graduates-work-ready-are-their-skills-transferable-into-the-workplace

Business of Fashion, BOF. (2020). *Careers.* https://www.businessoffashion.com/careers/

Cheng, S. (2018). The interdependence between the demand of fashion industry and the function of fashion education. *American Journal of Industrial and Business Management*, *08*(4), 1065–1072.

Clayton, P. R., & Clopton, J. (2019). Business curriculum redesign: Integrating data analytics. *Journal of Education for Business*, *94*(1), 57–63.

Daugherty, P. R., Wilson, H. J., & Michelman, P. (2019). Revisiting the jobs artificial intelligence will create. *MIT Sloan Management Review*, *60*(4), 1–8.

Denis, D. J. (2018). *SPSS data analysis for univariate, bivariate, and multivariate statistics*. John Wiley & Sons.

Dubreuil, M., & Lu, S. (2020). Traditional vs. Big-data fashion trend forecasting: An examination using WGSN and EDITED. *International Journal of Fashion Design, Technology and Education*, *13*(1), 68–77. doi:10.1080/17543266.2020.1732482

Ellington, T. N., Hahn, K., & McLeod, H. (2017). A case study: Fashion design and merchandising college core curriculum assessment to improve future learning. *International Journal of Home Economics*, *10*(1), 30–40.

Elrod, S. (2014). Quantitative reasoning: The next "across the curriculum" movement. *Peer Review*, *16(3)*, 4-8.

Fashion Schools. (2020). Top 50 fashion schools and colleges in the US - 2020 Rankings. Retrieved from https://www.fashion-schools.org/articles/top-50-fashion-merchandising-schools-and-colleges-us-2020-rankings

Francis, T., & Hoefel, F. (2018). True Gen': Generation Z and its implications for companies. McKinsey & Company. Retrieved from https://www.mckinsey.com/industries/consumer-packaged-goods/our-insights/true-gen-generation-zand-its-implications-for-companies

Giusti, J. D., & Alberti, F. G. (2018). Knowledge brokerage and creativity in a collaborative online innovation network of fashion makers. *Creative Industries and Entrepreneurship*, 101–118.

Grose, L. (2017). Fashion design education for sustainability practice: Reflections on undergraduate level teaching. In Gardetti, M. A., & Torres, A. L. (Eds.).*Sustainability in fashion and Textiles* (pp. 134–147). Routledge.

Ha-Brookshire, J., & Labat, K. L.2015). *Envisioning textile and apparel research and education for the 21st century*. International Textile and Apparel Association.

Hodges, N., & Karpova, E. (2009). Making a major decision: An exploration of why students enroll in fashion programmes. *International Journal of Fashion Design, Technology and Education*, *2*(2-3), 47–57.

Huberty, C. J., & Olejnik, S. (2006). *Applied MANOVA and discriminant analysis (Vol. 498)*. John Wiley & Sons.

Israeli, A., & Avery, J. (2017, May 30). *Predicting Consumer Tastes with Big Data at Gap*. Predicting Consumer Tastes with Big Data at Gap - Case - Harvard Business School. https://www.hbs.edu/faculty/Pages/item.aspx?num=52590

Jain, S., Bruniaux, J., Zeng, X., & Bruniaux, P. (2017). Big data in fashion industry. In IOP Conference Series: Materials Science and Engineering (Vol. 254, No. 15, p. 152005). IOP Publishing.

Johnson, L. (2012). Closing the loop: Using assessment results to modify the curriculum so that student quantitative reasoning skills are enhanced. *American Journal of Business Education*, *5(4)*, 465-468.

Kalbaska, N., & Cantoni, L. (2017, April). Digital fashion competences: Market practices and needs. In Kalbaska, N., & Cantoni, L. (Ed.). *Workshop on business models and ICT Technologies for the fashion supply chain* (pp. 125–135). Cham: Springer.

Landmark, A. D., & Sjøbakk, B. (2017). Tracking customer behaviour in fashion retail using RFID. *International Journal of Retail & Distribution Management*, *45*(7/8), 844–858. doi:10.1108/ijrdm-10-2016-0174

Lu, S. (2012). China takes all? An empirical study on the impacts of quota elimination on world clothing trade from 2000 to 2009. *Journal of Fashion Marketing and Management: An International Journal,16(3),* 306-326.

Lu, S. (2020). *2020 Fashion industry benchmarking study*. The United States Fashion Industry Association, Washington DC. http://www.usfashionindustry.com/pdf_files/20200731-fashion-industry-benchmarking-study.pdf

Luce, L. (2018). *Artificial intelligence for fashion: How AI is Revolutionizing the fashion industry*. Apress.

Lyu, J., & Leslie, C. A. (2017). The impact of study away in the fashion merchandising curriculum informed by student and alumni experience. In *International textile and apparel Association Annual Conference Proceedings* (Vol. 74, No. 1). Iowa State University Digital Press.

Marniati, & Witcjaksono, A. D. (2020). Curriculum implementation, entrepreneurship motivation, and fashion entrepreneurship-case study of student learning outcomes in regular classes and entrepreneurship classes. *International Journal of Fashion Design, Technology and Education*, 13(3), 317-324.

Miles, C. G. (2016). Mathematics proficiency of fashion marketing and fashion merchandising students. Doctor of Philosophy (PhD), Dissertation, STEM and Professional Studies, Old Dominion University, doi:10.25777/vgka-q953.

Milner, D. (2020, July 21). *Fashion jobs that are in demand now*. The Business of Fashion. https://www.businessoffashion.com/articles/intelligence/fashion-jobs-future-coronavirus-pandemic-digital-virtual-design-sustainability?utm_source=instagram

Moore, G. (2019, September 25). *Data Science: the impact of Big Data on the fashion industry*. The ID Factory. https://www.theidfactory.com/blog/data-science-the-impact-of-big-data-on-the-fashion-industry/

Ogle, J. P., Hyllegard, K. H., Rambo-Hernandez, K., & Park, J. (2017). Building middle school girls' self-efficacy, knowledge, and interest in math and science through the integration of fashion and STEM. *Journal of Family & Consumer Sciences*, *109*(4), 33–40.

Palomo-Lovinski, N., Copeland, L., & Kim, J. (2019). Perceptions of sustainability curriculum in US fashion academia. *International Journal of Fashion Design, Technology and Education*, *12*(3), 364–373.

Pasricha, A., & Kadolph, S. J. (2009). Millennial generation and fashion education: A discussion on agents of change. *International Journal of Fashion Design, Technology and Education*, *2*(2-3), 119–126.

Payne, A. (2016). Inspiration sources for Australian fast fashion design: Tapping into consumer desire. *Journal of Fashion Marketing and Management*, *20*(2), 191–207.

Radclyffe-Thomas, N. (2018). Designing a sustainable future through fashion education. *Clothing Cultures*, *5*(1), 183–188.

Richardson, T. (2019). The global Scapes of Postmodernity: A Proposed model for "global Cultural Flow" in fashion education. *Fashion Theory*, 1–17.

Robeck, J., & Pattison, A. (2013). The impact of fashion merchandising internships on careers. *Journal of Cooperative Education and Internships*, *47*(1), 31-46.

Schofield, L. S. (2012). Community-based learning versus traditional courses in statistics: Who takes them and why. *The American Statistician*, *66*(2), 118–123.

Schreier, M. (2012). *Qualitative content analysis in practice*. Sage publications.

Silva, E. S., Hassani, H., & Madsen, D. Ø. (2019). Big data in fashion: Transforming the retail sector. *Journal of Business Strategy*, *41*(4), 21–27.

Tiihonen, J., & Felfernig, A. (2017). An introduction to personalization and mass customization. *Journal of Intelligent Information Systems*, *49*(1), 1–7. doi:10.1007/s10844-017-0465-4

Varshney, L. R., Pinel, F., Varshney, K. R., Bhattacharjya, D., Schorgendorfer, A., & Chee, Y.-M. (2019). A big data approach to computational creativity: The curious case of Chef Watson. *IBM Journal of Research and Development*, *63*(1), 7:1–7:18. doi:10.1147/jrd.2019.2893905

Vicario, G., & Coleman, S. (2019). A review of data science in business and industry and a future view. *Applied Stochastic Models in Business and Industry*. 36(1), 6-18.

Waller, M. A., & Fawcett, S. E. (2013). Data science, predictive analytics, and big data: A revolution that will transform supply chain design and management. *Journal of Business Logistics*, *34*(2), 77–84. doi:10.1111/jbl.12010

Wang, B., & Ha-Brookshire, J. E. (2018). Exploration of digital competency requirements within the fashion supply chain with an anticipation of industry 4.0. *International Journal of Fashion Design, Technology and Education*, *11*(3), 333–342.

West, J. (2018). Teaching data science: An objective approach to curriculum validation. *Computer Science Education*, *28*(2), 136–157.

Yu, U. J. (2018). Examination of students' acceptance and usage of simulation software technology in an advanced-level merchandising class. *International Journal of Fashion Design, Technology and Education*, *11*(1), 1–11.

Yu, Y., Hui, C. L., & Choi, T. M. (2012). An empirical study of intelligent expert systems on forecasting of fashion color trend. *Expert Systems with Applications*, *39*(4), 4383–4389.

Zhong, Y., & Mitra, S. (2020). The role of fashion retail buyers in China and the buyer decision-making process. *Journal of Fashion Marketing and Management*, *24(4)*, 631-649.