

Fashion Printing Technology Diffusion: Big Data Analytics

Yanan Yu, Lisa Chapman, Marguerite Moore, North Carolina State University, USA

Introduction and Purpose

Defining the target market is a fundamental element of marketing strategy. To effectively target consumer groups, companies rely on marketing research to segment markets based on meaningful demographic variables (Summers et al., 2016). However, traditional marketing research methods (e.g. survey, interview) are limited in their ability to capture geographically dispersed consumer respondents. Widespread Internet use along with advances in data analytics facilitate data mining techniques that are capable of tracing online users' information. The purpose of this study is to identify the emerging market segments for an innovative technology in the fashion domain using social media based, big data analytics. Specifically, social media interaction among Twitter users engaged in digital printing technology (DPT) dialogue provides the research context for this study.

Literature Review and Theoretical Framework

Business practitioners and researchers have long been interested in the determinants of innovation adoption and dissemination. Roger's (1962) diffusion of innovations theory characterizes the innovation process as the collective dissemination of an innovation through communication channels over time within a social structure. As the theory evolved over time to incorporate multiple inquiry contexts, potential determinants of diffusion expanded to include characteristics associated with individual or organizational adopters and their respective environmental contexts (Wejnert, 2002). Rogers (2003) formally integrated a temporal dimension into his theory by determining that the *rate of adoption* tends to follow an S-curve distribution (Rogers, 2003). Based on diffusion of innovation theory, this study documented the diffusion of DPT in the U.S. in order to predict future diffusion of this emerging technology using big data analytics. The impact of potential adopter characteristics and their local business cultures on DPT diffusion at the state level was investigated to construct a predictive profile of likely DPT users.

Methodology

An AI-powered social media analytic software Crimson Hexagon was used to collect tweets that include the hashtag DPT from 2010 to 2019. R was applied to transform, clean, and quantify the occurrence frequency of tweets that explicitly refer to DPT. Occurrence frequencies over time for each year were subsequently plotted to visualize the dissemination curve, assuming that frequent tweets serve as a proxy variable for likely innovation adoption. Next, the data were organized into different geographical regions according to user-provided information. Tableau software was used to visualize DPT's geographical distribution and tweet density in each state over the past ten years.

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© 2020 The author(s). Published under a Creative Commons Attribution License (<u>https://creativecommons.org/licenses/by/4.0/</u>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. ITAA Proceedings, #77 - <u>https://itaaonline.org</u> To investigate potential predictors of DPT adoption, logistic regression was applied. Binary logistic regression facilitates prediction of dichotomous dependent variables (1= likely to adopt DPT, 0=not likely to adopt DPT). Demographics are classified *internal* factors within the study while business culture is considered as *external*. The model examined the impact of six demographic variables: working status (i.e., full-time employment percentage), financial status (i.e., household income), gender (i.e., female percentage), ethnicity (i.e., Caucasians percentage), education (i.e., bachelor degree percentage), and age distribution (i.e., youth percentage, ages from 19-34) among adopters. The demographic data for each state (2011-2018) were sourced from U.S. Bureau of Economic Analysis and U.S. Census Bureau. Based on previous research of DPT among social media networks which suggests that users are engaged in art and design communities (Yu et al., 2020), an additional external factor (i.e. art and design occupation annual median income) was integrated into the model.

Results

The diffusion of DPT suggests a non-linear pattern of adoption. In general, the discussion of DPT on Twitter appreciably emerged in 2011. While New York possessed the highest discussion volume, multiple local discussion hubs of DPT occurred at the same time in 2011 including: Massachusetts, Connecticut, Illinois, and Colorado. Then, the diffusion gradually expanded to other regions mainly on western and eastern coast and the annual discussion volume of DPT reached the first peak in 2013. From 2014, although the diffusion continued to spread to middle states (Missouri, Ohio, Tennessee) and south states (North Carolina and Texas), the total annual discussion volume of DP declined and did not exceed the first peak until 2017. From 2017 to 2019, the Twitter users who are interested in DPT became more geographically dispersed.

Results of the logistic analysis indicated that the seven-predictor model provides a statistically significant prediction for DPT adoption ($\chi^2(7, N = 408) = 125.33, p < .001$). The Cox and Snell and Nagelkerke pseudo R-squared values for the model are 0.264 and 0.354 respectively, which indicated good fit (Veríssimo, 2018). Classification accuracy was moderately high, with an overall correct prediction rate of 75.5 percent and correct prediction rates of 64.6 percent for adopting DPT and 84.1 percent for not adopting DPT. The area under the curve coefficient (AUC) was .799 (S.E. = .022), which illustrates reasonable discrimination ability of the logistic model. The results suggest that education, age distribution, financial status, and the environmental factor were statistically significant predictors of DPT adoption (Table 1). Additionally, while the bivariate linear test showed significant differences in gender, ethnicity and work status, the parameters of these variables are not significant in the regression model.

Discussion and Conclusion

This study is among the first to integrate big data analysis and regression analysis for examination of fashion technology diffusion. The results indicate that adopters may choose to reject a technology at one point in time only to adopt it at a later point, which appears to be consistent with Rogers's

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© 2020 The author(s). Published under a Creative Commons Attribution License (<u>https://creativecommons.org/licenses/by/4.0/</u>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. ITAA Proceedings, #77 - <u>https://itaaonline.org</u> assumption. Users who perceive short term risks are likely to postpone adoption. Future study should focus more on how to reinforce the adoption of emerging technology. Furthermore, the results suggest that DPT businesses can target media efforts to states with higher densities of likely adopters which tend to be more educated and younger. Interestingly, the results illustrate that states with higher household incomes are less likely to adopt DTG technology. Further study on this topic is recommended to include multi-group analysis across different levels of household income regions to probe this finding.

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Variables	Coefficient	S.E.	Wald	Exp (B)
Bachelor or higher degree ^a	.186***	.047	15.598	1.204
Youth ^b	.367***	.105	12.337	1.444
Household Income ^c	060**	.026	5.176	.942
Art & Design Income ^d	.118***	.033	12.337	1.125
Constant	-25.179**	11.801	4.552	.001

Table 1. Model's regression coefficients, the Wald test, significance, and odds ratio [Exp (B)].

Notes: 1) Level of significance: *p < 0.10, **p < 0.05 and ***p < 0.001; 2) Unit of variables a,b is percentage; unit of variables c,d are thousand dollars; 3) S.E. refers to Standard error; 4) Variables not present in the final model are omitted.

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