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Enhancing Chinese retail performance through digital transformation: The impact of employees analytics skills and data-based decision making

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Abstract— The present study analyses the potential of digital transformation to stand as a critical engine of competitiveness for traditional retail firms in China in the digital age. The research focuses on the relationship between two digital capabilities namely employees analytics and data-based decision making and two indicators of business performance in the digital world namely digital innovation dynamic and sales. The two-way MANOVA analysis was performed to analyze both individual and interaction effects of employees analytics skills and data-based decision making on digital innovation and sales performance. The result revealed non-significant multivariate and univariate impact of employees analytic skills on both digital innovation and sales while data-based decision making was found to exert a significant multivariate and univariate effect on the two outcome variables. Following up the significant multivariate effect, the discriminant function analysis revealed that sales performance considerably differentiated the different groups of data-based decision making.

Index Terms— Digital transformation, data-based decision making, digital innovation dynamic, employees analytic skills, data-based decision making, sales performance, traditional retail firm in China.

1 Introduction

Being largely used in the business context, digital transformation is also widely related to many other organizations in China such governments and private entities, in this study the term digital transformation will be related to the business perspective with focus on enterprises. According to [1], through the implementation of a culture of solid digital entrepreneurship China is expecting the fastest digital gains growth with US$527 billion against US$421 billion for the US and US$146billion for Japan. Core Chinese industries are already reaping the benefits of their digital transformation initiative, and their digital output could growth by 1.6 by 2020. Accenture presented the Digital output of the six core industries in China. Consumer Goods and Services ranked third with US$ 169 billion, Natural Resources second with US$ 188 billion, Auto, Industrial Equipment, Infrastructure and Transport ranked first with US$ 240 billion. Chinese consumption of digital technologies is leading to a shift in customers behavior pushing Chinese organizations to highly engage in digital transformation creating new opportunities. Realizing the potential of digital transformation for both public and private sector, the Chinese government implemented a "Digital China" plan. Through various national programs, the plan focuses on supporting industries and organizations in their digital transformation journey. Digital transformation is spreading around impacting all industries from manufacturing to banking, finance, health-care, utilities and so on. Yet the Retail industry is one of the faster changing in China. Digital transformation has a deep impact on the human element in organizations and its success relies on the digital agility of workers. This implies an efficient use of digital technologies and implementation of new strategies to better serve digital customer needs 26]. On the other hand, the introduction of new and fast-changing digital technologies in an organization usually crush with employees existing skills and capabilities, not in accordance with digital capabilities of the new ecosystem [16, 56]. Digital capabilities are skills that are needed to surpass simple information technology to include a wide range of digital constructs such as social media, mobile, and analytic skills to reap business value from big data. In the developing digital world, digital capabilities are key engines of business performance, they are key elements in reacting competition and the basis upon which organizations can develop existing products and services. Digital capabilities include the ability to build, integrate and reconfigure the organization' competencies to better address the digital changing ecosystem [34]. while employees of digital maturing companies are developing the digital required skills those of companies at the early stage of the journey experience more challenge to develop digital skills Kane et al. [33]. Capgemini Consulting and MIT Sloan [9] in a global survey reported that digital capabilities level and maturity differ across industries, high tech reported 38 % of digital maturity, 35% for banking, industry 12% and pharmacy 7%. as the human element and precisely employees are the key components of the organization, they constitute the organization's DNA just like the blood for human beings, it appears that powerful or successful business in the digital world goes along with the agile digital workforce. This study analyzes the potential of two digital capabilities namely analytics skills and data-based decision making on the performance of retail firms in China.

Despite the growing upshot of digital transformation in the Chinese retail industry, precedent studies tend to focus on the impact of big data on organization performance, while no empirical research emphasized the human element providing evidence of the role employees analytics skills and data-based decision making. This study covers this gap providing empirical evidence of the individual impact that both employees analytics skills and data-based decision making exert on enterprise performance. Furthermore, the present research considerably brings a new motion to the existing literature by analyzing the interaction effect of both employees' analytics skills and data-based decision making on organization digital innovation and sales performance.

In order to provide deeper insight, the remainder of the present study draws on the following structure: First, the literature review on the new skills of the digital age is presented leading to the formulation of our research hypothesis. The subsequent sections comprise the presentation of our research methodology, followed by the data analysis, result' s interpretation, discussion and finally our conclusion.

2 LITERATURE REVIEW

2.1 Employees analytics skills and firm performance

there should be a fit between individuals' skills and abilities and the requirements of their job [21]. When employees have the skills needed to fulfill job demands, they are more likely to perform at a higher level and are more highly committed to the organization [5]. From the information processing research stream initially introduced by [32, 42], Organizations face huge challenges related to the characteristic of data high in volume, velocity, and variety [31] and the use of analytics [19, 18, 17]. In the digital world, data are overwhelming and it becomes difficult for organizations to comprehensively process in-flowing information [22]. Such challenges obstruct their ability to effectively harness the economic value of business analytics [10]. It appears that traditional systems cannot catch, store, treat and analyze high variety, high velocity and large volume data [14, 52]; rather, this requisite innovative and new patterns of information processing talents. Based on the information processing research stream, it is supported that new skills such as information processing capabilities are needed in order to overcome these challenges and [10] pointed that these new capabilities create value and positively impact the effectiveness of decision making in organizations. The information processing perspective puts emphasis on the necessity of fitting information processing skills with the information processing needs of the digital era. Wang et al. [23] substantiate this view posing that there is a positive relationship between information processing abilities and performance. Consequently a firm is expected to experience more effectiveness whereas its information processing skills are adjusted to its information processing requisites [42]. In the digital age, analytics skills are vital as they increase customer understanding which is a key driver of retail business success, retailers can obtain high benefits from getting more insight of changing customers of the digital world [15]. The capacity to obtain and analyze customer information is fundamental for building strong customer loyalty as using even offline research tools, customer delivers mass information that can be used to understand their interest and preferences meanwhile leading to the creation of impacting customer experience that will increase sales [4].

From the resource fit view [38], It is supported that through data analytics brings value on firm performance [40], better capture of this value requires an association of various organizational resources such as the data itself, the analytic tools and most importantly the employee's analytic skills [38]. Accenture [1] defined employees analytics skills as the employees capacity to find, manage, manipulate, analyze and interpret data. Despite existing challenges related to their analytics investments, increasingly companies acknowledge that analytics talent such econometric skilled, statistical experts and decision scientists remain the most difficult to find and yet constitute a prerequisite to effectively compete in nowadays market place and furthermore they believe that these capabilities can allow them to reach a high level of differentiation, generate prescriptive and predictive insight [1]. Analytics skills are accessed as being among of the most important skills in the 21 century [14], they enhance the firm ability to comprehend the new digital world [41], allow insight and hidden information discovery and it has become a powerful construct that increasingly companies are leveraging to gain competitive advantage as it brings the opportunity to obtain more accurate details about their clients, their preferences, personal information, shopping behavior, all usable as catalyst to lunch new products and boost sales [53].

Hypothesis 1: Employees analytics skills have a positive impact on firm digital innovation and sales performance

2.2 Data-driven decision making and firm performance

The digital transformation going along with the evolution of information technology, big data, and business analytics, has contrived a new level of decision making in firms, allowing leaders to have a deeper view of their organizations and business activities [18]. Cao et al. [10] defined data-based decision-making as the extent to which a business is willing to adopt new ideas challenging current processes, practices and based on data- insight. Data based decision process allows firms to reach a high level of flexibility [51], and significantly reduce costs [10]. In the digital world, enterprises are leveraging data-based decision strategies to gain economic benefits and enhance innovation [53]. Data management skills are vital for firms in the digital age as turning data into valuable business information has the potential to increase business efficiency Westerman et al. [54]. Data based decision-making and data mindset help to vanish the organizational impediments and barriers that obstruct information sharing, tighten relation with customers, draw deeper customer insights, increase market power and drive profitability [1]. Moved towards data-driven and information insights, the new shape of decision-making leveraged through digital transformation brings forth the proliferation of opportunities, generates value, develops competitive advantage, increases enterprise efficiency and most importantly leads to the creation of new products and services for customers [50, 19, 47].

Hypothesis 2: data-based decision making has a positive impact on firm digital innovation and sales performance

2.3 Integration of Analytics skills and data-based Decision making for firm performance

Based on business analytics perspective [20], information processing capabilities of an organization can be defined as the firm ability to prehend, incorporate and information and data, and use the gained insights in the context of corporate decision-making. Premkumar et al [27] argue that the synergy of information processing requisites, information processing skills and information-based decision making has an evidentiary effect on firm performance. Capitalizing analytics relies on hiring analytics skilled employees, but the challenge for leaders remains about how can organizations make them productive [53]. Analytics skills do not generate business value on their one and their business influence lies on many other resources and constructs of the firm [44] such decisions making Radhakrishnan et al. [46]. The study of Accenture [1] suggests an integrated analytics journey strategy starting with detecting the business issue, defining the appropriate analytics talents and finally re-engineering the decision making apparel through the spreading of analytics skilled employees into business unit to enhance the use the analysis results and insight. Analytics skills find their real value only once their are integrated and took into consideration to make intelligent decisions [53]. The arduous challenge firms meet in their analytics journey is not truly related to the hiring of analytics skilled employees, but rather on infusing, tying and fitting analytics into decision making practices as this strategic integration of both can deliver greater business value, increase organization's performance, reduces risks, drive customer loyalty and increase the firm ability to innovate in the digital world [1].
Hypothesis 3: Employees analytics skills and data-based decision making have an interaction effect on firm digital innovation and sales performance

3 METHOD

3.1 Participants

Our research was carried among retail firms across China, selected companies were all born before the 2000s and included Chinese owned, foreign subsidies and Chinese foreign-owned business. Data collection was supported by survey conducted from March to Mai 2019, with management assistance and support of a retail digital transformation organization, questionnaires were addressed to top leaders, in some cases to chef of human resources or to chief digital officers. On a voluntary basis companies leaders completed the survey and were asked to describe the level of their employee's digital capabilities. The survey was anonymous and the questionnaire did not require leaders to provide their personal identification or any other identifying information of their firm except the geographic localization and their branch of activity.

3.2 Measures

Our study is built on four variables, among which two independent variables representing digital capabilities namely, data-based decision making and employees analytic skills. For leaders to describe these abilities in their firms, 1 to 5 measurement scale was used, 1= "very poor" level of employees digital capabilities and skills, 2 = " poor", 3 = "average" level, 4 = "good" level and finally 5 = "very good" level of employees digital skills. Digital innovation dynamic and sales performances represented our two dependent variables. For digital innovation performance and sales performance, 1-5 measurement scale was used where 1= "very poor", 2 = " poor", 3 = "average", 4 = "high"and 5 = "very high".

3.3 Analysis procedures

This study is built upon a two steps procedure.
1) Two-way MANOVA: Addressed firstly by Wilks [55], the MANOVA procedure is nowadays widely recognized and frequently used in diverse research spheres ranging from social science to biology [58, 11]. Two-way MANOVA analysis is a multivariate analysis of variance testing the hypothesis that two or more predictor variables have impact on a group of two or more outcome variables [3] with the primary purpose of detecting and understanding the simultaneously or the interaction effect of the predictor variables on the dependent variables [48]. Precisely in this study, the two way MANOVA analysis allows us first to analyze the individual impact of the independent variables on the two dependent variables, second to analyse the interaction effect of predictors on the dependent variables [37], third by the use of the contrast analysis to evaluate the difference across groups [24] in terms of digital innovation and sales performance based on their level of digital capabilities. When having numerous dependent variables, researchers can decide to perform just one multivariate test or to run few numbers of multivariate test [3, 28, 29, 30] discussed further this issue. This study uses IBM SPSS Statistics 23 to run two-way MANOVA analysis. The Two-way MANOVA analysis is performed for data-based decision making and employees analytic skills on the dependent variables digital innovation and sales performance. Alan Taylor [3] suggested a method of calculation of the effect size based on the idea that the following formula [(1 – Wilks' Lambda) * 100] could be considered, but [13] supported that this value in intuitively stupendous and thus imparted other measures among which the Partial Eta squared η^2, retained as measure of effect size in this study and significance of these effects will be based on "p"value.
2) Discriminant Function Analysis: Kieffer et al. [36] supported that most of the researchers who used MANOVA also used univariate F tests, Tukey tests and Scheffé as Post-hoc analyses, but [57] found that these approaches focus on group differences while failing to take into account the contribution of the outcome variables, for this reason, authors such [46] strongly disdained researchers who simply used separate univariate test after a significant multivariate. Further, [49, 8, 6] all agree that the discriminant function introduced by Fisher [25] could be considered over F test as follow up of significant result of MANOVA. Considering all the precedent the Discriminant Analysis appears to be the best way of following up significant MANOVA analysis [24], it allows to analyze group differences with regard to a set of outcome variables [43] and through

only one procedure it provides the possibility to detect the variables that contribute the most to separate the predictor groups [57] and Garry Chick 2010). Discriminant Analysis Function will be carried in this study and will allow understanding how the dependent variables digital innovation and sales performance individually discriminate the different groups of Data-based decision making. Discriminant analysis function will not be performed for employees analytics skills due to insignificant univariate and multivariate effects.

4 RESULT

4.1 Assumption of multivariate analysis

1) Dependant variables measurement and Test of normality.
The first assumption of two-way MANOVA is related to the measurement of the dependent variables as they are required to be continuous but Laerd [36] indicated that if the measurement scales have five values the data can be thus treated as continuous. Table 1 of descriptive statistics show that both digital innovation and sales performance are based upon five scales measurement. Table 2 exhibits the normality test output where all the results are statistically nonsignificant with regard to the p values all greater than 0.5, so we assume normality and we can stand that digital innovation and sales performance are both normally distributed. Additionally, looking at the residual statistics in table 3 we can see that the maximum Mahalanobis distance value is equal to 13.38. As the critical value for Mahalanobis distance value is 13.82 we confirm the normality because 13.38 < 13.82.

TABLE 1
DESCRIPTIVE STATISTICS

	N	Minimum	Maximum	Mean	Std. Deviation
Sales performance	300	1	5	2.21	.406
Digital innovation Performance	300	1	5	2.04	1.150
Employees Analytic Skills	300	1	5	2.06	1.203
Data Based Decision Making	300	1	5	2.15	1.221

TABLE 2
TEST OF NORMALITY

	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
Digital Innovation Performance	.237	300	.202	.813	300	.401
Sales Performance	.488	300	.202	.497	300	.563

a. Lilliefors Significance Correction

TABLE 3
RESIDUAL STATISTICS[a]

	Minimum	Maximum	Mean	Std Deviation	N
Mahal. Distance	.378	13.389	1.993	2.416	300

TABLE 4
CORRELATIONS

	Digital Innovation Performance	Sales Performance
Digital Innovation Performance	1	.606**
Sales Performance	.606**	1

***. Correlation is significant at the 0.01 level (2-tailed).*

2) Test of multicollinearity
Looking at table 4 we notice that between digital innovation and sales performance the correlation coefficient = 0.6 and as long as it is < 0.9 and > 0.2 we can assume that the two variables are correlated enough but not multicollinear, consequently, the multivariate analysis can be conducted.

3)Test of Homogeneity
Named after Box [7], the Box's M test analyzes the equality of covariance matrices, from output table 5 we notice a non significant result with p = .106 which is > .05, due to this insignificant result we fail to reject the null hypothesis and we assume that the covariance matrices of the dependent variables are equal across groups, more precisely we can stand that the assumptions of equality of covariance matrices and homogeneity have been met.

TABLE 5
BOX'S TEST OF EQUALITY OF COVARIANCE MATRICES[a]

Box's M	77.729
F	2.267
df1	27
df2	1093.330
Sig.	.106

Tests the null hypothesis that the observed covariance matrices of the dependent variables are equal across groups.[a]
*Design: Intercept + Data based decision making + Employees analytic skills + Data based decision making * Employees analytic skills*

4.2 Multivariate test

The output of the multivariate test in table 6 shows that significant main effect is found for data-based decision making where Wilks' Lambda Λ = .530, F(8,550) = 25.64, p = .000, therefore we reject the null hypothesis that the combination digital innovation and sales performance is equal for all levels of data-based decision making and retain the alternative hypothesis to stand that this combination of the two dependent variables will differ according to the level, as suggested by [13], multivariate effect size is represented by the Partial Eta Squared (η^2 = .27) . No significant main effect for employees analytic skills with Wilks' Lambda Λ= .645, F(8,550) = 16.86, p = .085, consequently we tend to reject the alternative hypothesis and assume the null hypothesis to support that the combination of digital innovation and sales performance is equal for all different levels of employees analytic skills. Finally the result shows a statistically significant interaction effect between data-based decision making and employees analytic skills on the combination of digital innovation and sales performance where Wilks' Lambda Λ= .775, F(30,550) = 2.49, p = .001 with effect size η^2 = .12. The Levine's test of equality of variances for our two outcome variables is exhibited in table 7 and we notice that both results are statistically nonsignificant where digital innovation performance shows p = .071 and sales performance p = .205.

TABLE.6
MULTIVARIATE TEST

Effect		Value	F	Hypothesis df	Error df	Sig	Partial Eta Square
Intercept	Pillai's Trace	.959	3235.868b	2.000	275.000	.000	.959
	Wilks' Lambda	.041	3235.868b	2.000	275.000	.000	.959
	Hotelling's Trace	23.461	3235.868b	2.000	275.000	.000	.959
	Roy's Largest Root	23.461	3235.868b	2.000	275.000	.000	.959
Data based decision making	Pillai's Trace	.471	21.229	8.000	552.000	.000	.235
	Wilks' Lambda	.530	25.643b	8.000	550.000	.000	.272
	Hotelling's Trace	.883	30.247	8.000	548.000	.000	.306
	Roy's Largest Root	.881	60.792c	4.000	276.000	.000	.468
employees analytic skills	Pillai's Trace	.357	14.980	8.000	552.000	.063	.178
	Wilks' Lambda	.645	16.865b	8.000	550.000	.085	.197
	Hotelling's Trace	.548	18.780	8.000	548.000	.092	.215
	Roy's Largest Root	.544	37.524c	4.000	276.000	.016	.352
Data based decision making* employees analytic skill	Pillai's Trace	.234	2.434	30.000	552.000	.000	.117
	Wilks' Lambda	.775	2.498b	30.000	550.000	.001	.120
	Hotelling's Trace	.280	2.561	30.000	548.000	.021	.123
	Roy's Largest Root	.235	4.325c	15.000	276.000	.000	.190

a. Exact statistic
b. Computed using alpha = .05
c. The statistic is an upper bound on F that yields a lower bound on the significance level.
*d. Design: Intercept + Data based decision making + Employees analytic skills + Data based decision making * Employees analytic skills*

TABLE 7
LEVENE'S TEST OF EQUALITY OF ERROR VARIANCES[a]

	F	df1	df2	Sig.
Sales performance	17.076	23	276	.205
Digital innovation performance	1.955	23	276	.071

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.[a]
a. Design: Intercept + Data based decision making + Employees analytic skills +

4.3 Univariate test

Moving to table 8 we can observe the results of the univariate test. Indeed Tests of Between-Subjects Effects shows that digital innovation and sales performance are separated, so it is not the combination of the two any longer, and we can see the relationship between data-based decision making and each of the outcome variables separately. We notice a statistically significant result of data-based decision making on digital innovation performance with p = .000 and η^2 = .10; this means that digital innovation performance varies significantly across data-based decision-making levels more clearly that there is significant difference between data-based decision-making levels in terms of digital innovation performance. The same assumption is retained for sales performance with p = .000 and η^2 = .46, suggesting that sales performance differs significantly across data-based decision-making levels. Just like in the multivariate test, employees analytic skills do not show any statistically significant univariate result for both digital innovation (p = .431) and sales performance (p = .206); thus we can stand that both digital innovation and sales performance do not differ based on employees analytic skills. Furthermore, looking at the combination of data-based decision making and employees analytic skills we have a statistically significant effect for both outcomes variables where the p-value of digital innovation performance equaled .044 and the effect size η^2 = .07 and p value of sales performance equaled .000, η^2 = .18.

TABLE 8

TEST OF BETWEEN-SUBJECTS EFFECT

Source	Dependent variable	Type III Sum of Squares	df	Mean Square	F	Sig	Partial Eta Square
Corrected model	Digital innovation performance	152.425a	23	6.627	7.524	.000	.385
	Sales performance	37.135b	23	1.615	36.977	.000	.755
Intercept	Digital innovation performance	862.502	1	862.502	979.250	.000	.780
	Sales Performance	276.501	1	276.501	6332.465	.000	.958
Data based decision making	Digital innovation performance	27.397	4	6.849	7.776	.000	.101
	Sales Performance	10.484	4	2.621	60.024	.000	.465
Employees analytic skills	Digital innovation performance	44.927	4	11.232	12.752	.431	.156
	Sales performance	5.721	4	1.430	32.754	.206	.322
Data based decision making *Employees analytic skills	Digital innovation performance	20.193	15	1.346	1.528	.044	.077
	Sales performance	2.731	15	.182	4.170	.000	.185
Error	Digital innovation performance	243.095	276	.881			
	Sales performance	12.051	276	.044			
Total	Digital innovation performance	1644.000	300				
	Sales performance	486.000	300				
Corrected total	Digital innovation performance	395.520	299				
	Sales performance	49.187	299				

a. R Squared = .385 (Adjusted R Squared = .334)
b. R Squared = .755 (Adjusted R Squared = .735)
c. Computed using alpha = .05

TABLE 9

CONTRAST RESULT (K MATRIX)

Data Based Decision Making Simple Contrast[a]			Dependent Variable: Digital innovation performance	Dependent Variable: Sales performance
Level 1 vs. Level 5	Contrast Estimate		-1.373	-.800
	.Hypothesized Value		0	0
	.Difference (Estimate - Hypothesized)		-1.373	-.800
	.Std. Error		.266	.059
	.Sig.		.002	.000
	.95% Confidence Interval for .difference	Lower Bound	-1.898	.917
		Upper Bound	-.849	-.683
Level 2 vs. Level 5	Contrast Estimate		-1.284	-.792
	.Hypothesized Value		0	0
	.Difference (Estimate - Hypothesized)		-1.284	-.792
	.Std. Error		.283	.063
	.Sig.		.000	.004
	.95% Confidence Interval for .difference	Lower Bound	-1.841	-.916
		Upper Bound	-.728	-.668
Level 3 vs. Level 5	Contrast Estimate		-.841	-.536
	.Hypothesized Value		0	0
	.Difference (Estimate - Hypothesized)		-.841	-.536
	.Std. Error		.321	.072
	.Sig.		.009	.000
	.95% Confidence Interval for .difference	Lower Bound	-1.474	-.677
		Upper Bound	-.209	-.395
Level 4vs. Level 5	Contrast Estimate		-.585	-.288
	.Hypothesized Value		0	0
	.Difference (Estimate - Hypothesized)		-.585	-.288
	.Std. Error		.293	.065
	.Sig.		.491	.361
	.95% Confidence Interval for .difference	Lower Bound	-1.162	-.416
		Upper Bound	-.009	-.159

4.4 Analysis of groups difference

As we found statistically univariate significance for data-based decision making leading to the assumption that the level of data-based decision making has an impact on the firm digital innovation and sales performance, next we are interested in finding how the differences occur among different levels. Looking at the results of the contrast analysis in table 9 we realize that when comparing companies that have a very poor level (1) of data-based decision making to those of a very strong level (5), there was significant difference in both digital innovation ($p = .002$) and sales performance ($p = .000$). Looking at the comparison between those having poor level (2) and those having a very high level (5) we also notice that significant difference exists in terms of digital innovation ($p = .000$) and sales performance ($p = .004$). Comparing level (3) to level (5) we also find significant difference for digital innovation ($p = .009$) and sales performance ($p = .000$). while all the precedent comparisons among groups show significant difference, the comparison between level (4) and level (5) do not show any significant difference both for digital innovation ($p = .491$) and sales performance($p = .361$). This implies that companies that have a strong level of data-based decision making and those having a very strong level tend to not differ in terms of digital innovation and sales performance.

4.5 Discriminant function analysis

The output of table 10 exhibits each variate ' s eigenvalue. Eigenvalues can be converted to express the percentage of variance accounted for,we can notice that the first variate accounted for 99.8% of the variance while the second variate accounted only for .2%. Furthermore, this output exhibits the canonical correlation that can be squared and used as an indicator of effect size. The output of table 11 exhibits the results of the significance analysis of both variates. Fist, the entire model is tested as a whole including both variate 1 and variate 2 ('1 through 2'), then after that, the first variate is pulled away leaving behind the second variate ('2'). When variate 1 and variate 2 were combined together the two variates significantly discriminated the levels ($p =.000$), but when testing variate 2 alone it appears to be nonsignificant ($p =.872$). Therefore, the group differences shown by the MANOVA can be explained in terms of two underlying dimensions in combination.
The coefficients in the structure matrix in table 12 show how each variable contributes to the variates. We can see that digital innovation and sales performance all have positive relationships with the first variate, whereas sales performance shows the strongest relationship with a value of 1 while digital

innovation performance shows a weaker relationship with a value equaled to .467, thus variate 1 can be assessed as differentiating digital innovation from sales performance. In contrast, looking at the second variate, digital innovation performance shows a strong positive relationship with .886 while sales performance expressed a weak negative relationship with -.009. Variate 1 differentiates data-based decision-making levels through some factors affecting sales performance differently than digital innovation and this differentiation is only related to effect size, whereas variate 2 differentiates data-based decision-making levels through dimension affecting digital innovation and sales performance in a different way and in different directions.

The standardized discriminant function coefficients detect whether or not an outcome variable significantly brings contribution to the composite (Alan Taylor, 2011). The exhibited in table 13 join the contribution size of sales performance and digital innovation on the variate, just like the structures matrix suggested, sales performance shows the strongest contribution to variate 1 with a positive weight .995, digital innovation despite the positive sign of the weight has the weaker contribution .010. In the second variate, digital innovation has the strongest relation with positive weight 1.123 while sales performance shows a medium negative relationship -.520. We conclude that in the second variate data-based decision-making levels differences can be found in the opposite direction of sales performance and digital innovation performance.

TABLE 10
EIGENVALUES

Function	% of Variance	Cumulative %	Canonical Correlation
1	99.8	99.8	.736
2	.2	100.0	.049

a. First 2 canonical discriminant functions were used in the analysis

TABLE 11
WILKS' LAMBDA

Test of Function(s)	Wilks' Lambda	Chi-square	df	Sig.
1 through 2	.457	231.519	8	.000
2	.998	.707	3	.872

TABLE 12
STRUCTURE MATRIX

	Function	
	1	2
Sales Performance	1.000*	-.009
Digital innovation performance	.463	.886*

TABLE 13
STANDARDIZED CANONICAL DISCRIMINANT FUNCTION

	Function	
	1	2
Sales Performance	.995	-.520
Digital innovation performance	.010	1.123

TABLE 14
FUNCTIONS AT GROUP CENTROIDS

Data Based Decision Making	Function	
	1	2
Very poor	-.620	.029
Poor	-.565	-.002
Average	.399	-.092
Strong	1.857	-.053
Very strong	2.872	.093

Output 14 of the variate centroids of each level shows that the first variate discriminates those having a very poor and poor level of data-based decision making to those having average, strong and very strong level because very poor and poor level both show negative values respectively -.620 and -.565, whereas average, strong and very strong all show positive values on variate 1 respectively .399, 1.857 and 2.872. This implies that function 1 separates those having poor very poor level (with high negative centroid values)to those having average, high and very high level of data-based decision making (with high positive centroid values).

5 Summary of Result

Using Wilks' Lambda, no significant multivariate effects were found for employees analytic skills. In contrast there was a significant effect of data-based decision making on the combination of digital innovation and sales performance $\Lambda = .530$, $F = 25.643$, $p = .000$, and significant interaction effect of the combination of employees analytic skills and data-based decision making $\Lambda = .775$, $F = 2.498$, $p = .001$. The effect size of data-based decision making alone was stronger $\eta^2 = .27$ than the effect size of the combination of both data-based decision making and employees analytic skills $\eta^2 = .12$. The univariate ANOVA analysis on the dependent variables exhibited significant effects of data-based decision making on sales performance $F = 60.024$, $p = .000$ and digital innovation dynamic $F = 7.776$, $p = .000$. a significant effect is also found for the combination of employees analytic skills and data-based decision making on both digital innovation $p = .044$ and sales performance $p = .000$. The univariate test also revealed that the effect size of data-based decision making on sales performance was stronger $\eta^2 = .46$ than on digital innovation $\eta^2 = .10$. The same phenomenon was observed for the combination of data-based decision making and employees analytic skills where the effect size on sales performance equaled .18 while digital innovation recorded .07. Discriminant analysis was used to follow up The MANOVA, revealing two discriminant functions. The first function explained 99.8% of the variance, canonical R2 = .45, whereas the second explained only .2%, canonical R2 = .03. In combination the two discriminant functions differentiated significantly data-based decision making levels , $\Lambda = .457$, $\chi^2 (8) = 231.519$, $p = .000$, but pulling away function 1 indicated that function 2 alone did not differentiate significantly data-based decision making making, $\Lambda = .998$, $\chi^2 (3) = 0.707$, $p = .872$. The correlations between dependents and the discriminant functions showed that sales performance loaded highly on the first function (r = .995) than on the second (r = -.520) while digital innovation performance loaded highly on the second function (r = 1.123) than on the first function (r = .010).

6 Discussion

The present study reveals that unlike data-driven decision making, employees analytic skills across business do not appear to be a key driver of performance as our analysis showed that digital innovation and sales performance did not differ based on firm's employee's analytic skills. But an interesting finding was the interaction effect found for data-based decision making and employees analytic skills on both digital innovation and sales performance. This implies that in the digital world, traditional retail businesses can adopt the association of data-driven decision making and employees analytic skills as a strategy in order to raise their competitiveness, overcome the new business rules introduced by retail digital natives and catch up the new retail dynamic of the digital age. Another point worth precision is that looking at the test between subjects, data-based decision making and the integration of employees analytic skills and data-based decision making all showed a greater impact on sales than on digital innovation. The same phenomenon was observed through the discriminant analysis where the variable sales performance loaded more in differentiating the different groups of data-based decision making. This leads us to assert that despite their data-based decision making and employees analytic skills maturity level, traditional retail firms in China are still struggling to improve their digital innovation dynamic, understanding the digital innovation dynamic across these firms will constitute the of our future research.

7 Conclusion

The primary objective of this research was to examine the individual impact of data-based decision making and employees analytic skills and their interaction effect on both digital innovation and sales performance in 300 traditional retail firms in China. In retail firms born before the 2000s and considered as non digital natives, it appears that leveraging a strategy that integrates employees analytics skills to data-based decision making can be considered as an engine of performance and competitiveness. Our study provides evidence that companies leveraging digital transformation and capabilities are more likely to experience digital innovation and sales growth and performance. Giving the new challenges of the digital age, firms that do not apply or lightly apply this strategy could possibly experience poor performance of digital innovation and sales.

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