Consumer Behavior and Image Analysis: A Student Customer Retention Model

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Customer retention is a critical strategic marketing concept, regardless of industry. This study examined customer defection within a postsecondary educational system, operationally defined as student retention-risk. The process involved utilizing image analysis of student ID cards by assessing facial micro-expressions with an artificial intelligence program developed by employing a series of machine learning algorithms. Discriminant findings suggest one sentiment, [Degree of Happiness] as expressed in a student's university ID card, will identify students at-risk, potentially enhancing Return on Marketing Investment (ROMI) with strategic intervention. Results highlight an Intervention Table, as well as a Summary Table utilizing the acronym SMILE.

Keywords: image analysis, customer retention, Return on Marketing Investment (ROMI), customer satisfaction, student retention

INTRODUCTION

Customer satisfaction and retention are well researched and critically important issues for both practitioners and academics. There are models and frameworks proposed that help explain the effects of satisfaction on retention (Rust & Zahorik 1993), the efficacy of customer relationship management tactics (Verhoef 2003), and other meaningful influences that may predict retention (Gustafsson, Johnson, & Roos 2005). Yet these challenges persist across industries, organizations, and institutions; principally with customer defection. Ultimately, this lost customer or client is concomitant with a company's loss of revenue, which supports the organizational structure and function (Rust & Zahorik, 1993).

Also, there are ancillary problems associated with this customer defection, for example, the inability to generate future customer referrals (Ganesh, Arnold, & Reynolds, 2000; Verbeke, Dejaeger, Martens, Hur, & Baesens, 2012; McKnight, Paugh, Frey, & Song, 2019). Moreover, to sustain growth and profitability, a marketer must now create aggressive strategies for customer replacement. This replacement cost is expensive and time-consuming as previous market research indicates customer acquisition strategies typically cost more than customer retention strategies (Colgate & Danaher, 2000; East, Hammond, & Gendall, 2006).

Cook and Talluri (2004) suggested that marketers have been slow to leverage their ability to maximize their long-term outcomes, specifically what happens to a customer once they appear at an organization, institution, or shop. Cumming (2014) elaborated on this phenomenon by stressing that marketers should utilize the conceptual framework of Return on Marketing Investment (ROMI) – a comprehensive process that is as much a strategic challenge as it is a tactical one. This ROMI, as a strategic process, looks as much to customer attraction as it does to customer defection. As Powell (2008) demonstrates in the *Marketing Calculator*, it is common to waste or mismanage half your marketing and advertising resources since it is unknown which half of your customer base is likely to defect.

With this issue in mind, the current research aims to reveal methods of identifying potential antecedents to customer retention and defection at the onset of the customer relationship, and to utilize this knowledge in conjunction with existing literature to posit retention strategies and tactics to address customer satisfaction in a population that is more likely to need such efforts. Also, although there are debates regarding the student as a customer, there is a consensus that students demand superior customer treatment or else an institution can expect student departures resulting in retention issues (Gonzalez, 2016). This research examines if an institution of higher education can potentially improve ROMI by early identification of students at-risk for departure.

LITERATURE REVIEW

The marketing literature provides several relevant studies in many contexts that detail and classify the components of customer-risk (see Buckinx & Van den Poel, 2005; Lemmens & Croux, 2006; Risselada, Verhoef, & Bijmolt, 2010). Research threads on student retention have included examining the roles of strong advising (Nealy 2005), pre-entry interventions (Thomas 2011), developmental mathematics and English courses (Wood 2016), and the predictability of standardized tests in predicting successful outcomes (Williams, Smiley, Davis & Lamb 2018). However, a real limitation with retention research is the timeframe between customer identification and customer intervention strategies. This significant gap in time is true for all industries, including higher education institutions focused on the critical issue of student retention.

Effective marketers understand that customers require a quick resolution to their needs, or their institution will face a retention-risk (McLauchlin, 2010). However, there is a paucity of research addressing the timeframe between assessing needs and the intervention. For example, administering a student success or environmental climate survey in higher education is common, yet the timeframe between administration, scoring, distribution, and eventual intervention could take longer than a student's decision to leave. However, officials do have a critical facet of student information instantly available to them, which requires minimal lag time between administration and distribution. This potentially valuable piece of information is the student Identification Card (ID) frequently taken weeks before university classes begin.

Photo Identification (ID) cards are ubiquitous in society and serve as a face-to-face authentication method. Public and private corporate entities, as well as primary, secondary, and postsecondary institutions, issue an array of photo ID cards. Photo IDs typically allow entrance or privilege, but there are other possible applications of this device that may be valuable to academic researchers and marketing managers.

A systematic and comprehensive review of research in the business, marketing, psychology, and higher education marketing journals uncovered no directly applicable research findings in the area of photo ID research. This dearth of research is an obvious area of need given the powerful capabilities and continued advancements of artificial intelligence (AI), machine learning, neural networks, and clustering algorithms. Although in an interesting conceptual twist, Landwehr, McGill & Herrmann (2011) examined how people decode emotional "facial expressions" from product shapes, finding that people anthropomorphize objects, and this process affects the liking of design. Thus, in the auto industry, an upturned grille, like the smile it resembles, conveys a friendly behavioral predisposition, whereas a downturned one conveys an aggressive behavioral predisposition. Therefore, it is conceivable that examining human facial expressions by image analysis, if consistent and conceptually valid, may have the potential to increase ROMI. A recent application of AI models to facial image analysis demonstrated that machine learning has an error rate of less than five percent, lower than estimates given for the human eye (Kumar et al., 2019).

DERIVATION OF HYPOTHESES AND QUESTIONS OF INTEREST

Historically, the literature addressing retention in higher education marketing utilized descriptive summaries of why a student decides to leave (see Bean, 1980; Tinto, 1987; Braxton, Sullivan, & Johnson, 1997; and Bean & Eaton, 2000). This research examines if there are efficient and valid procedures to identify at-risk students by assessing the feasibility of image analysis. Specifically, the purpose of this research is to develop and test a prediction model that minimizes the timeframe between identification and intervention strategies for students deemed at-risk.

There are six research questions examined in this exploratory research.

Q1: *Can image analysis discern an algorithm when examining Student ID micro-expressions that will predict retention-risk?*

Q2: *Can image analysis examining micro-expressions, identify by category, which emotional state(s) as expressed in a Student ID predict retention-risk?*

Q3: *Can image analysis detect a significant difference in the primary emotion expressed in a Student ID between Male and Female when predicting retention-risk?*

Q4: *Can a specific emotional state, as expressed in a Student ID, predict retention risk if quantified?*

Q5: *Can a curvilinear relationship between the emotional state expressed in a Student ID predict retention-risk over and above any linear relationship?*

Q6: *Can a hit-ratio (discriminant analysis) determine the validity of image analysis when predicting retention-risk?*

METHODOLOGY

Facial expressions exhibit two operational classifications: 1. "Posed"; and 2. "Spontaneous" (Ekman & O'Sullivan, 1991). This study utilized the "Posed" Student-ID photo, based on the assumption that this type of photograph reflects a "student's feelings/thoughts" about attending college. The N-size was 240, divided initially into two equivalent participant clusters of 120 for an A/B comparison. Group A contained sixty student photo IDs (n = 60) who left the university; and, sixty student photo IDs (n = 60) who remained at the university following their first-year college experience. This process resulted in a discriminant analysis yielding a prediction formula for empirical cross-validation with a holdout group (N

= 120). This holdout or Group B also contained two equivalent participant clusters of student photo IDs: those who left (n = 60) and those who remained at the university (n = 60).

The researchers developed a facial recognition, sentiment analysis computer program utilizing ten thousand faces in a machine learning model, a form of artificial intelligence (AI), that, through "training," recognized the probability of seven expressed emotional states: Happiness; Sadness; Surprise; Neutral; Anger; Disgust; and Fear. This image analysis by sentiment breakdown controlled for researcher bias since the algorithm scored all emotions. By process, the program uses OpenCV to perform facial recognition, and it uses a Convolutional Neural Network (CNN), trained on a modified version of the FerPlus emotion dataset from Microsoft. The image has transforms applied to it (such as brightness, rotation, etc.) before the CNN processes an image. The CNN then decides appropriate emotions expressed. As researched, assessing emotional content is possible with voice (El Ayadi, Kamel, and Karray, 2011), but as Davidson et al. (1990) introduced, using facial expression by microexpression analysis forms a simpler and more powerful technique of recognizing emotions (see Figure 1).

FIGURE 1
AI IMAGE ANALYSIS: EXAMPLE OF EMOTIONAL RANGE DETECTED

Note. A sample stock photo found in *Training Deep Networks for Facial Expression Recognition with Crowd-Sourced Label Distribution* (Barsoum et al., 2016). Retrieved January 3, 2020, from https://arxiv.org/pdf/1608.01041.pdf

The program assigned a probability rating regarding the type of emotion expressed on a one hundred-point scale, with 1 = lowest probability and 100 = highest probability. Researchers operationalized this probability as the "Degree of Happiness" expressed. Researchers set the Alpha level at .05.

RESULTS AND DISCUSSION

The first question determined if image analysis could discern an algorithm when examining Student ID micro-expressions to predict retention-risk. Results yielded no statistical significance ($Df = 1, 9$; $F = .23$; $p = .64$), likely a function of n-size. The population ($N = 120$), when examined, expressed only four emotions of the seven possible [Happiness, Sadness, Neutral, Anger] occurring nine times; hence, there were 24 possible algorithms with nine images sharing the same algorithm. Therefore, there is insufficient power to detect significance if it exists; thus, no ability to discern an algorithm of best-fit.

The second question tested if image analysis examining micro-expressions could categorically identify which emotional state(s) as expressed in a Student ID would predict retention-risk. Results were statistically significant ($Df = 1, 115$; $F = 11.06$; $p = .001$) suggesting that expressed "Happiness" predicts retention-risk, that is, increasing the probability of detecting if a student plans (consciously or unconsciously) to depart or remain at the university. Thus, an enrollment manager or market researcher can assess the degree of Happiness expressed in a Student ID card and develop a customer-retention plan as warranted, given the categorical assignment.

The third question investigated if image analysis could detect a significant difference in the primary emotion expressed in a Student ID between Male and Female, when predicting retention-risk – yielded no statistical significance (Df = 1, 115; F = 2.80; p = .09). The primary sentiment, as expressed by either Male or Female, does not differ significantly, implying no correction or adjustment is necessary. The researcher may reasonably assume the micro-expressions to be equivalent when predicting retention-risk between genders.

The fourth question focused on if a specific emotional state, as expressed in a Student ID, could predict retention-risk if quantified (follow-up of question 2) – results were statistically significant (Df = 1, 115; F = 16.86); p = .0001). The degree of expressed Happiness (0 - 100%) could predict the level of retention-risk. For clarification, as expressed "Happiness" increases, so does the probability of retention. Thus, an enrollment manager or market researcher can assess Happiness expressed in a Student ID card and develop a customer-retention plan as warranted, given the categorical assignment. Furthermore, from the regression model and findings, a student/customer must express Happiness at a minimum level of 68%; below this level (cut-point), there is an increase in retention-risk. Therefore, the construction of a decision tree or intervention table is possible and can be a feasible/usable technique for screening retention-risk. Thus, a customer-retention plan, if strategic and timely, should improve the probability of enhancing ROMI.

The fifth question proposed that a curvilinear relationship between the emotional state expressed in a Student ID could predict retention-risk over and above any linear relationship. The curvilinear model did not account for a significant amount of variance over and above the variance accounted for by the linear relationship (p = .66). Thus, for marketers, utilizing the linear relationship to forecast student-risk, is both pragmatic and predictive.

The sixth question sought to confirm by discriminant analysis if a hit-ratio would establish the practical validity of using image analysis when predicting retention-risk. Operationally, the hit-ratio is the percentage of successes in prediction, to the total number of observations. The higher the hit ratio validates any prediction model. For example, if the model successfully predicts 34 customers are a retention risk out of the 50 who departed, the hit-ratio would be 68% for predicting those customers who leave. Likewise, if the model successfully predicts 44 customers that are no retention risk out of the 50 who remained, the hit-ratio would be 88%; for a combined hit-ratio of 78%.

For this study, findings suggest that the hit-ratio resulting from the discriminant analysis provides an acceptable level of validity when forecasting student retention-risk. These results indicate an overall successful hit-rate of 70% using a linear prediction model. Thus, results indicate that image analysis is a valid technique with wider application beyond a post-secondary student population (see Table 1).

TABLE 1
DISCRIMINANT ANALYSIS: HIT-RATIO

Predicting Customer Retention-Risk	*Formula Development Group 1*	*Validity Test Group 2 (linear - Q4)*	*Validity Test (curvilinear, 3rd Degree Function - Q5)*
Stay vs. Leave	**Hit-Ratio: Group 1**	**Hit-Ratio: Group 2**	**Hit-Ratio: Group 2**
Predicted "No-risk" - Stay	0.63	0.67	0.66
Predicted "At-Risk" - Leave	0.73	0.76	0.63
Overall: Hit-Ratio	**0.68**	**0.72**	**0.64**
Cumulative Hit-Ratio	*0.70*		*0.64*

Note. Group 1, N = 115; with five IDs eliminated because the students never attended the university; used to develop the discriminant function, predicting stay or leave (retention-risk). Group 2, random selection, N = 120 (n = 5 randomly eliminated to match Group 1 n-size). Group 2 used to test the predictive validity of the risk assessment; results confirm using the linear over the non-linear function (Fourth Column).

An ancillary finding suggests that students failing or choosing not to take a photo ID were a retention risk – 11 of 11 withdrew; the statistical probability of this outcome occurring by chance is 0.0005.

There are five key findings of this research. First, a happy student (as expressed in their Student ID) has a high probability of retention. Second, students who miss or fail to take a photo are a high retention risk. Third, image analysis is an efficient method to assess the level of at-risk students. Fourth, losing a customer increases replacement cost with a lost opportunity for customer referrals. Fifth, to increase ROMI, using image analysis as a strategic marketing tool is reasonable. Table 2 summarizes the findings and implications of this exploratory research.

TABLE 2
SUMMARY OF FINDINGS: 'SMILE'

Smiling student = anticipated happiness = high probability of retention
Missing or failing to take the photo = a high probability of retention-risk
Image analysis = quick identification method to determine at-risk students
Lost customer = increased replacement cost = lost opportunity for referral
Enrich ROMI = with at-risk intervention = a strategic marketing analysis

LIMITATIONS AND FUTURE RESEARCH

This research proffered several unique findings and important implications for student retention initiatives; however, the sample size was insufficient to test the feasibility of using or developing a comprehensive algorithm for prediction. Moreover, this study utilized a convenience sample, that is, a university student population possessing a Student ID. Therefore, the generalization of results without further replication is tenuous. Similarly, students can stop-out or transfer, only to return in a later semester; thus, the opportunity for initial misclassification exists.

Other potential limitations exist with the picture taking process itself; for example, did the picture take place pre or post-university orientation? Did a student have an orientation at all? How did the photographer set-up or stage the picture? For clarification, some Student IDs had students looking at something other than the camera.

The assumption that image analysis may materially improve ROMI needs further testing across business sectors and industries. Since many diverse organizations in highly competitive markets like health clubs and warehouse retailers use identification cards, testing the ability to identify at-risk customers and assess strategic interventions appears warranted if revenue growth, profitability, and enhanced ROMI are strategic imperatives.

Finally, this research utilized computer software programming and machine learning with a discriminant function to predict retention-risk; however, is it possible for an individual marketing manager or team of researchers to discern visually, without computer assistance, the "degree of happiness" expressed in an ID card? This human type of factor intervention warrants further study, as well as innovative conceptual frameworks considering the student's culture, race, religion, or cognitive profile regarding expressed emotions.

CONCLUSION

For clarification, image-analysis does not replace any conventional or institutional specific means of identifying students at-risk for leaving an institution. Image-analysis, as a process, offers an additional strategic marketing intervention to increase ROMI by developing mathematical algorithms to assist with student/customer retention. Future research may discern additional options that this research did not highlight, that is, given the ever-expanding role of artificial intelligence, machine learning, and micro-expression analysis.

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