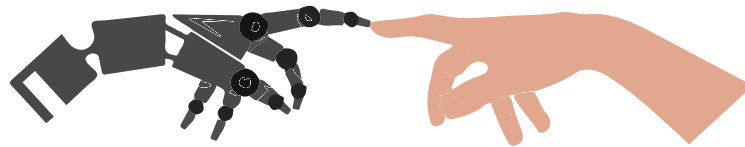


AN OVER VIEW ON CONSULTING

Networked Collaborative AI Agents



netAIsys

AI Driven Networked Company

Division of

CRMportals

Business Intelligence



A Sample of Advanced Analytics Projects

-Members of CRMportals Inc. and Institute of Analytics(USA)™ Tea

Industry	Data Required	Sample KPIs for Prediction
Financial services (B2C) Retail Banking, insurance, investment services	See some of the case studies discussed to see how different data sets were used; structured and unstructured data	<ol style="list-style-type: none"> Retention, acquisition, cross-sell/up-sell, innovative products and services, expected economic values, elasticity models NBO (Next best offer) – Banks typically have lots of different products. NBO is a serious challenge for any bank. Also, train the organization on the value of analytics
Travel/Entertainment (Customer Intelligence)	Customer complaints and sentiments using unstructured data vs. structured data	In a large conglomerate of network of hotels, analysis of direct input at the front desk of their needs vs. input in text format regarding their stay experience and segmentation of priority areas (“Themes”) to address the opportunity areas. We also compared this with their survey data. This led to some important measurements in controlling social media expressions and validations
HR/Talent Management Acquisition of new talents, retention, and expected value of the talents and networks	Resume, application data, HRIS system available data, social data, geo-demographic, sociographic data; structured and unstructured data	<ol style="list-style-type: none"> Lifetime value of a candidate to the organization, (2) Likelihoods of ‘culture and communication coefficients’ on key human capital indices, (3) likelihoods of technical superiority, (4) likelihoods of social and emotional IQ, (5) network influence measures of employees
Health Analytics (Direct to patient, Direct to physician, Quality Metics, Post Phase III CT), Pharma Marketing, Outcome research, hospital analytics, populationa and sub-population comparisons, side effects, and epidemics)	Claims data, insurance premium, coverage; medication/instruments/facility utilization data; hospital data; admissions and outcomes; geo-demographic, sociographic data; structured and unstructured data	Predictive models for (1) hospital infections, (2) likelihoods of readmission, (3) likelihoods of patient quality service and patient satisfactions. Performance and influence measures for Partner and physician services

Case 1

Next Best Offer - Banking Application

Geo-demographic data



Transactions Data



Campaigns Data



Survey data

HCAMPS Survey		Survey Instructions	
<p>SURVEY INSTRUCTIONS</p> <ul style="list-style-type: none"> This should only be used if you were the patient during the hospital stay reported in the cover letter. Do not fill out this survey if you were not the patient. Answer all the questions by choosing the box to the left of your answer. You get extra points for skip your some questions in this survey. When this happens you will see an asterisk to indicate that you skipped a question. Please note, skip this: <ul style="list-style-type: none"> <input type="checkbox"/> Yes <input type="checkbox"/> No <input type="checkbox"/> If No, Go to Question 1 <p>For the number of questions you skip, this number is added to the total score of your survey. For example, if you skip 3 questions, your score will be 3 points higher than the actual score. Please note, skip this: <ul style="list-style-type: none"> <input type="checkbox"/> Yes <input type="checkbox"/> No <input type="checkbox"/> If No, Go to Question 1 </p> <p>Please answer the questions in this survey about your stay at the hospital covered in the cover letter. Do not include any other hospital stays in your answers.</p> <p>YOUR CARE FROM NURSES</p> <p>1. During this hospital stay, how often did nurses treat you with kindness and respect?</p> <p><input type="checkbox"/> Never <input type="checkbox"/> Sometimes <input type="checkbox"/> Usually <input type="checkbox"/> Always</p> <p>2. During this hospital stay, how often did nurses (staff) explain to you what you needed to do?</p> <p><input type="checkbox"/> Never <input type="checkbox"/> Sometimes <input type="checkbox"/> Usually <input type="checkbox"/> Always</p> <p>3. During this hospital stay, how often did nurses (staff) explain to you what you needed to do?</p> <p><input type="checkbox"/> Never <input type="checkbox"/> Sometimes <input type="checkbox"/> Usually <input type="checkbox"/> Always</p> <p>4. During this hospital stay, how often did nurses (staff) explain to you what you needed to do?</p> <p><input type="checkbox"/> Never <input type="checkbox"/> Sometimes <input type="checkbox"/> Usually <input type="checkbox"/> Always</p>		<p>5. During this hospital stay, how often did nurses (staff) explain to you what you needed to do?</p> <p><input type="checkbox"/> Never <input type="checkbox"/> Sometimes <input type="checkbox"/> Usually <input type="checkbox"/> Always</p> <p>6. During this hospital stay, how often did nurses (staff) explain to you what you needed to do?</p> <p><input type="checkbox"/> Never <input type="checkbox"/> Sometimes <input type="checkbox"/> Usually <input type="checkbox"/> Always</p> <p>7. 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Additionally, we have also executed projects that required propensity and brand models for a number of industries, combining geo-demographic data, transactions data, campaigns data, and survey data



Institute of Analytics (USA)™
Big Data Intelligence Training

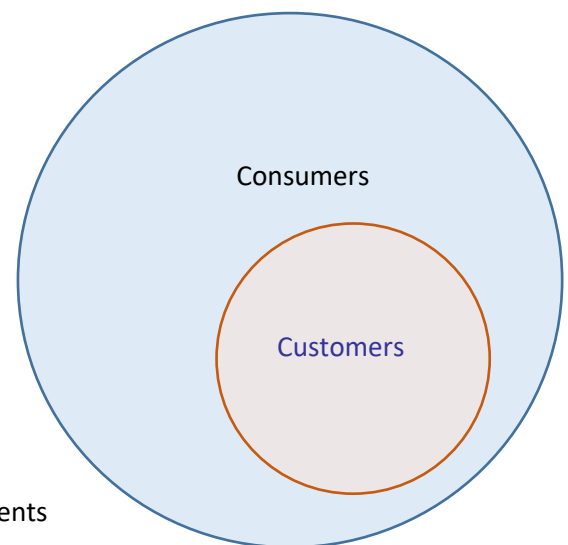
Nethra Sambamoorthi, PhD
Founder and Managing Director

Usable Data for Propensity Models and Next Best Offer Models

Customer Intelligence Applications and Consumer Applications

Common variables list that are useful for brand and product propensity models, Next Best Offer are the following. I use consumer to distinguish from customer as some one who is not the current customer but belong to the population who is likely to become a customer. Depending on acquisition model or loyalty models, the corresponding subpopulation will be scored.

- A.** Customer data internal to the franchise (A)
- B.** Customer transaction data elements (B)
- C.** Customer campaign data – promotions and responses (C)
- D.** Partner transaction data of the customers (D)
- E.** Partner campaign data – promotions and responses (E)
- F.** Customer survey data – attitudes and preferences (F)
- G.** Franchise product codes, and product category codes (G)
- H.** Consumer/customer geo-demographic-sociographic data elements (H)



To understand, in USA context, the national consumer database of geo-demographic-sociographic data, see NY Times article on a expository article. <http://www.nytimes.com/2012/06/17/technology/acxiom-the-quiet-giant-of-consumer-database-marketing.html>

Transaction data and campaign data are internally available data in an organization or technically belongs to the franchise

Case 2

Themes in Unstructured Customer Input - A Comparison of Direct Input vs. Social Media Input

Unstructured Customer Input in Hotel Industry - Text analysis of social media

Customers provide input in various ways and one of the important ways that is common recently, is taking social media to express their experience about their stay. To a large extent, because of anonymity of the person, what they provide in social media have larger variation of emotional expressions with many shades.

Client also receives input at the front desk. Often the customers see the immediate benefits speaking with the front desk and their text/verbal inputs with tone and body language are very subtle. So the client wanted to compare the overall segmentation ("Themes") in the trends of the direct input vs. social media expressions

Customer Input in Hotel Industry - Text Analysis

Client provided data on direct input vs. social media based input, collected from Twitter and Facebook.

We did segmentation analysis ("Themes") of direct input of text/tone/body language vis-à-vis social media analysis.

The trend analysis of these themes and their divergence or convergence between these two channels of input were used in understanding the customers and service at the counters as well as the customer perception of the status of the properties. Accordingly, the client was able to prioritize the work areas for faster and better ways of benefitting from customer input for corrective priorities and increased positive customer experiences.

The client mentioned that the analysis provided a deeper connection to their customers and now they have a better control of the social media channel for competitive operations

Case 3

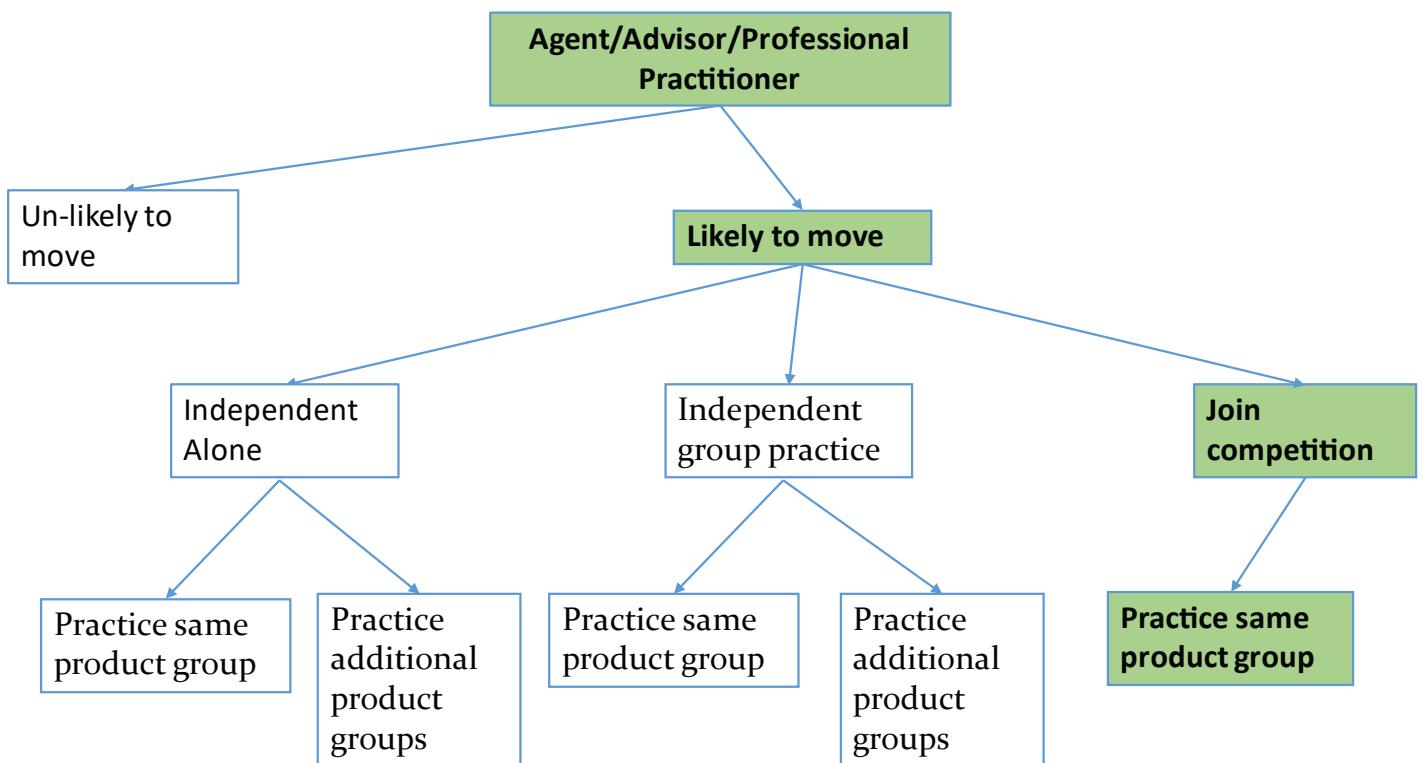
Mover Model and Mover's Next Action

Sales/Advisor Mover Model and the Expected Business To Gain (to Loose)

Which Advisor (Investment Services or Insurance or financial advisor or professional practice) is likely to move out (ideal for acquisition/retention - depending on who is acting) of franchise sales network and how much portfolio value will be lost (gained)?

- This integrated two predictive supervised models
 - Move vs. Not-Move model and subsequent action nodes
 - AUM (Assets under management) model
- Based on this predictive model, client was able to target so well that they finished their year-long advisor's acquisition plan in 3 months
- Additionally, the top two investment advisors brought in \$500 million dollars of worth of AUM
- The client was saying that this was their best work in the last 30 years and it was a news article
- Subsequent to this, the consulting practice was able to sell 5 similar projects among investment services companies in six months

TARGETS FOR ACQUISITION and RETENTION



Data Sources

- Investment advisor professional data from SEC.GOV
- Investment advisor geo-demographic data from data accumulator
- Census block level data

Variations of this type of model is usable in any sales network or professional groups (insurance agents/physician practice group/financial advisors/sales professionals)

Case 4

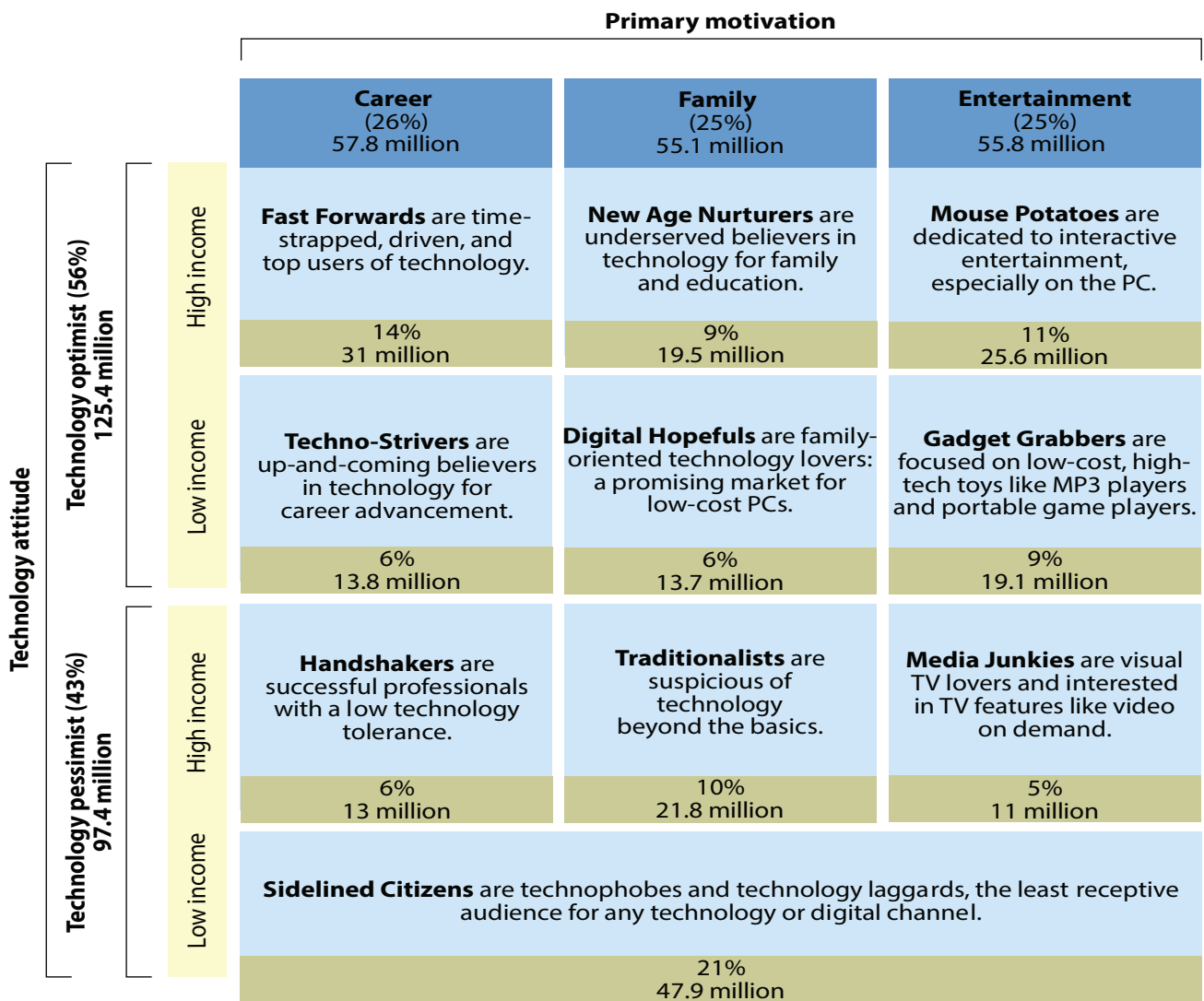
Strategic Segmentation for a top Technology Company for Strategic Planning and for 1to1 CRM

- The client is a top 5 technology company interested in converting a strategic marketing segmentation scheme into a 1-1 CRM applicable classification scheme
- Marketing segmentation schemes are macro level schemes, and are not applicable at individual level for B2C applications
- Having a million plus dollars segmentation scheme, but usable only for strategic directional applications and not one to one tactical CRM applications is a common problem in marketing
- The client wanted to convert their strategic segmentation scheme for 1-1 tactical CRM applications
- Data Sources:
 - The client provided their segmentation scheme and wanted to create rules for projecting the segmentation scheme at individual consumer level
 - comScore click data (a select balanced national representative of 100,000 individual (web) surfers data was used to enhance with
 - Geo-demographic third party data (having 1000+ variables)

Impact CRM Application - Projection of Multi-Class Strategic Segmentation Scheme

- We used multiple predictive methods such as discriminant analysis, multinomial logistic, and random forest with boosting to build this supervised projection algorithm
- In a 10 class applications, the algorithm was predicting 2.5 times better in the top three key segments compared to the random occurrence. For 290 million plus accounts, this provided opportunity to work with 121 Million higher income accounts accurately to support a one-one CRM relationship.

Forrester Technographics® Segmentation Scheme

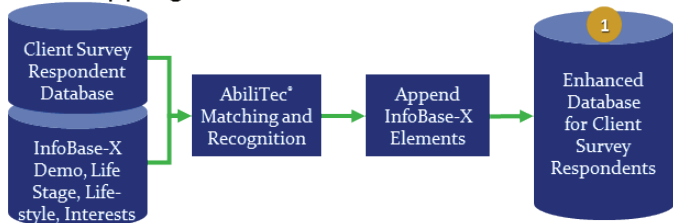


Base: 37,226 US individuals

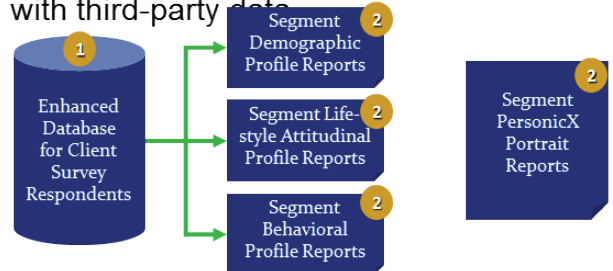
*Percentages may not equal 100% because we did not include those who didn't respond to all included questions
Source: North American Technographics Benchmark Survey, Q2 2010 (US, Canada)

CBAT - A National consumer database, Survey Research Infused Targeting Approach

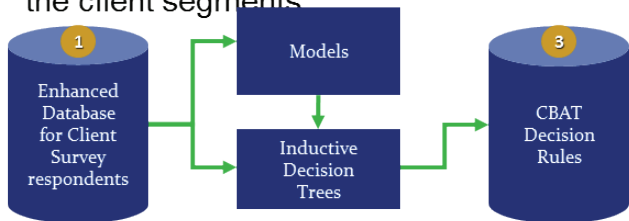
- 1. Match client survey respondents with InfoBase-X and enhance with demographic, life stage, lifestyle, interest and general retail shopping behavioral information**



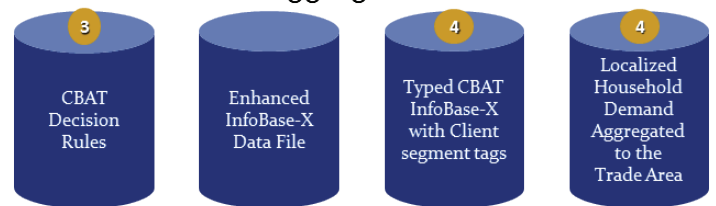
- 2. Generate segment portrait reports using appended InfoBase-X variables and PersoniX Life Stage Clusters integrated with third-party data**



- 3. Develop hybrid classification models, a combination of logistic regression models and decision trees, to establish a mapping relationship from InfoBase-X data element to the client segments**



- 4. Apply the decision rules from the decision rules to map the InfoBase-X population. Each household is assigned to one client segment. Scored national household file aggregated to the trade areas**



In a live executives present, in-house in-presentation testing, our algorithm identified correctly, 8 out of 10 times!

Case 5

Auto Insurance Loyalty Program Management

- The client was losing close to 15% every year in their auto insurance account base
- The Senior Management asked for a customer intelligence based loyalty program management to improve loyalty of the customers. The client had million plus auto insurance accounts at any point in time.
- The client premium base was close to 4 Billion dollars in today's dollars
- We selected balanced sample of current customers and the customers who left the organization in the last six months
- Hired a sample survey organization. We collected behavioral and attitudinal survey data from these accounts. We also collected data on claim experience, premium data from internal systems, customer experience data.

Impact

- Client Improved Annually 2% in their Retention Efforts in dollar terms
- In today's dollar terms, it is \$30 Million dollars in premium impact with close to 20,000 accounts, annually.

Case 6

Leveraging Pharmaceutical Product Marketing Addressing Privacy Concerns

Patient Acquisition and Patient Loyalty Program

- The direct to patient communications, approved by FDA raised opportunities for pharmaceutical manufacturers to do direct marketing to patients.
- The lifestyle product manufacturer was one of the first and we had the opportunity to work on this innovative, as the first to address the market for a lifestyle product
- Privacy issues were the concerns of the client, the industry, and the government organizations
- We invented a way of getting complete personal information without violating the confidentiality of PII in the work processes
- This facilitated the ability to figure out look-alike members of lifestyle product users, in the national database

Patient Acquisition and Patient Loyalty Program...Continued

- Crunching 55 Million select records with 1000 plus geo-demographic, socio-graphic variables, we were able to come down to 1 Million records where we were able to net close to 330,000 actual product users.
- This resulted in the net market yield of \$45 MM in today's dollars on the acquisition side, as a one time yield.
- This one time analytics impact was accruing with an annual yield of \$30 million dollars on the compliance side, until further revisions

Case 7

A vast collection of Regular Student Projects

A Sample Collection of Joint Works on the Academic Side With One of The Latest Term...

Click on the embedded PDF document below, which will open the full document – The Student Project Experiences are Widely Distributed on Topics

Nethra Sambamoorthi, Ph. D
Lead Faculty, School of Professional Studies
Master of Science in Predictive Analytics
Northwestern University, Evanston, IL

Spring 2016 - LIST OF CAPSTONE PROJECTS PREDICT 498 – Instructor and Project Advisor - Nethra Sambamoorthi, Ph. D

Number	Team Name	Topic Name	Communication/ Analytics Lead	Data/Analyst Lead1	Data/Analyst Lead2	Data/Analyst3 Lead
1	Georgia	Bundling Products – A New Growth Strategy Using Term Deposit and Credit Cards at the PNC Bank	Adeline Rassas	Sung Park	Joshua Peng	Travis Sari
2	California	Designing Marketing Strategies and Solutions for KaVo Kerr Group, A Global Dental Products Company	Stephen Smirl	Alex Thomas	Matt Cormett	Nagabrintha Thiru Sridhar
3	Hawaii	Health Disparity Analysis of Lead Poisoning Levels In Chicago Housing Market	Anne Seaman	Carlos Ardilla	John Nation	Bradley Price
4	Illinois	Analyzing Suitability of EMA401 as Viable Replacement for Opioid Medications	Dominick Tornabene	Paul Lee	Rita Petherbridge	Ni Ni Tint