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Human Centered Predictive Customer Science

Bridging Sales, Process Excellence and Customer Science

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Abstract

Customer Science is a new field that combines AI, behavioural science and data analytics. The goal of customer science is to make models that are adaptable, accurate and specific to each customer. These models will improve both customer involvement and business outcome. The study will look at how customer science methods can be used in several important areas. It will do this by using real life business problems that we have seen in sales operations, customer success and process excellence. I am going to talk about the Human Centered Predictive Customer Science model (HCPCS), which is a new way to combine feedback loops, behavioural pattern and CRM automation. I will show that the HCPCS model can work by looking at two EdTech case studies that focuses on improvement of Net Promoter Score (NPS), converting leads and lowering loss. I will include results from experiments, tables, success metrics.

Keywords: Customer Science, Predictive Analytics, CRM Automation, Churn Prediction, NPS Improvement

1.Introduction

Customers used to passively take in information, but now digital markets have changed that so now they actively create the value. Because businesses are getting bigger, it's getting harder to give people experiences that are both personalised and quick. This paper will use cases from two different jobs as Sales Manager/Customer Success and Process Excellence Manager, to show how Customer Science can be used to drive growth in the long term.

Customer Relationship Management (CRM) systems are no longer helpful in detail because customers want personalized services and one that respond to their needs in real time. This makes the field of Customer Science necessary. This field is growing and includes behavioural economics, data science, artificial intelligence and journey designs to build customer systems that are scalable and emotionally intelligent.

This study shows both the theory and practice of using customer science framework. It does this by giving companies a way to use data driven approaches to make their customer centricity better. This dissertation starts with a literature review of the basic ideas behind customer science. It then moves on to propose the HCPCS model and prove its validity using real life case studies and supporting data.

The result in this paper helps two kinds of groups: academic researchers who wants to base models of customer behaviour on real business environments and practioners who wants to use proven methods to consistently improve their customer satisfaction, trust and retentions rates.

2. **Literature Review and Theoretical Foundations**

We will talk about the main theoretical bases for Customer Science in this part. We will show how behaviour (what people do), psychology (how people feel), marketing (how people react) and data (trends) all fit together. By doing this, we will lay a good basis for the HCPCS framework that comes next in this dissertation.

2.1. **Customer Science Defined**

A report from McKinsey & Company in 2022 [6] says that customer science is the combination of behavioural science, data analysis and AI to give customers experiences that are both personalized and automatic. It talks about the challenges with general marketing and how people desire experiences that are more relevant and personal.

Harvard Business Review (2020) says that how people feel about buying products is a big part of how well it knows what customer wants. We need to look at both their behaviour and their emotions. So, these two sources shows that in today's market, a good customer experience needs to be based on data, emotions and should also be backed by technology.

2.2. **Behavioural Economics and Nudge Theory**

Thaler and Sunstein's book Nudge (2008) [5] are the well-known starting point of the field. They describe how people can use shortcuts to figure things out, like "rules of thumb", which can lead them to regularly erroneous judgments. The main theme of the book is nudge theory, which suggests that small but well-designed changes to how choices are presented, "choice architecture" to the authors, can assist people make better choices without taking away their freedom.

2.2.1. **Common examples of nudges used in customer experience include**

a) **Timed reminders**: Making people aware of their task at the right time is enough to get them to finish it. In Australia, text messages reminded people to fill out their welfare forms on time, which led to more people doing so.

b) **Default Options**: Most people just make the usual choice when its already there. A huge number of people get stuck with "no utensils" when it was the usual setting on the food apps.

c) **Social Proof Nudges**: To get people to do what one wants then to do, tell them what other people do. This is called social proof nudges.

d) **Gamified Milestones and Feedback**: Give people more small prizes, progress bars or fun messages to keep them going.

2.2.2. **The Effectiveness of Nudges Has Been Proven Through Many Studies**

a) **E-Commerce Nudges**: To help with e-commerce, digital nudges like showing popular items or sorting by default can be useful. One can also make it easy to find a way around and increase the number of sales.[10]

b) **EdTech Nudges**: Like reminding students of future classes, made students much more interested over the course semester.[4]

c) **Health Nudges**: Making vaccine appointments automatically booked increased vaccination rates much higher than self-scheduling systems. [14]

2.2.3. **How This Relates to HCPCS**

All the nudge types outlined above relate to core components of HCPCS:

1. Customers come back at the best time when they are reminded.
2. Social proof nudges build trust and community.
3. Users are more likely to use something when it has defaults and success markers.

So, HCPCS uses evidence-based nudge methods to improve both customer experience and result by adding behavioural techniques to the CRM workflow and the customer journey stage. This supports a personalized, proactive and scalable customer experience model.

2.3. **Customer Journey Mapping and Friction Points**

Lemon and Verhoef (2016) [8] say that the current customer journey is not simple at all. Customers no longer go straight from one step to the next. Instead, they go through a lot of different digital and real touchpoints. This trip has three main parts: during the purchase, during the purchase and after the purchase. Each part is shaped by a mix of emotional responses, logical thinking and normal patterns of behaviour.

2.3.1. **Important Insights Include**

a) **Multi-Touch Point Environment & Fragmentation**: Customers today find brands on the web, social media, in shops or through chatbots. To give customers a smooth and uniform experience, all the company's team must work together. This because customers interact with the company in many ways.

b) **Friction Points**: These are the issues that slow down the customer's journey, like replies that take too long to come back, texts that are hard to understand or a refund process that is hard to understand. To make it easy for customers to go from being interested to being loyal, one should find and fix these problems.

c) **Chances After Engagement**: These are important steps along the way, like taking the first trial class, checking out or getting a return. Lots of customers say this about the business and how they are with it. [1]

2.3.2. **Why this relates to HCPCS**

a) **Identify Friction**: We can see where customers stop or lose interest by making a map of their trip. For example, many people quit after filling out the trial form or don't show up for their first lesson. With tools like Airtable, it's easy for HCPCS to find these trouble spots.

b) **Engagement Cadence Optimization**: we follow up with a customer to close the feedback loop after calling them. Customer will be happy and NPS will go up because we showed we heard them and did something about it.

c) **Predictive Analytics and Machine Learning**: In the past, CRM systems put customers not groups and tried to guess what they would do next by using simple data mining and statistical techniques like decision tress and grouping. Machine Learning and Deep Learning were used in new systems to make faster, better and more accurate guesses in real time.[15]

2.3.3. **Some core areas include**

a) **Real-Time Behaviour Classification**: Machine Learning models like random forests, gradient boosting and neural networks help sort people into groups based on what they do online, like when they log in to LMS, open emails or click on certain pages. The things that people do are put into groups that businesses can use.

b) **Churn Prediction**: ML and Deep Learning models can figure out ahead of time which will people are likely to stop using a service. With the help of 240 studies, these advanced models were found to be the most accurate at predicting decline.[11]

c) **Customer Lifetime Value (CLV) Modelling**: CLV provides an idea of how much money a customer might bring in the future. Companies can now focus more on their most important customers. When ML is added to survival analysis and regression models, the results are better for selling more content or coaching sessions.

d) **Next-Best-Action (NBA) Decision Engines**: Tools like Pega's NBA Advisor tells what's the best next step is with the customer, like offering a discount, setting up a call with a guide or sharing a tutorial. These ideas come from how the customer acts now and how they have behaved in the past.

2.3.4. **These capabilities are critical to HCPCS**

a) Behaviour analysis let us personalize and divide work in real time.
b) Churn alerts let us take actions early on, like sending a WhatsApp message or calling to teach someone before the person stops using the service for good.
c) CLV score helps put resources where they are needed the most.
d) NBA suggestions help team members make decisions by pointing out the best thing to do.

2.4. **CRM and Process Automation**

According to Salesforce (2023), 68% of high performing businesses now use AI driven CRM workflows to reduce manual dependency and personalised outreach. [2]

2.4.1. **Core Functions Relevant to this Study in CRM include**

a) Automated lead movement
b) Engagement scoring
c) Tracking response times
d) Nudging follow up's
e) Routing feedback

These features store data and give operational information, which is a lot like using predictive customers science on a large scale.

3. **Methodology**

There are both quantitative and qualitative data from a study that goes on for up to 12 months that are used in these dissertations. This is called Mixed Methods Research Designs. With this method one can keep the track of small details of how customers act and the measurable results of the changes one makes to the business.

3.1. **Research Design**

The study is structured around two embedded case studies across edtech organisations: Company 1, Company 2. Each case involved an intervention based on the HCPCS framework Implemented through iterative design, feedback and outcome measurement.

3.2. **Data Collection Methods**

a) Quantitative Metrics

* CRM Logs and Dashboards (HubSpot, AISensy)
* Conversion Rates (%), Churn Rates (%), NPS Scores, Time-To-Resolution (Hours)
* Campaign Response Analytics (Email Open Rates, WhatsApp Reply Tags)

b) Qualitative Metrics

* Conversations with school counsellors and customer success managers
* Analysis of parent and student comments by theme
* Notes from escalation checks and weekly reviews of operations

3.3. **Data Analysis Techniques**

a) Use descriptive statistics to see how KPI changed before and after a change
b) Cohort analysis is used to keep track of groups of learners over time in churn prediction models.
c) Behavioural segmentation is used to group customer journeys and types of interaction into different groups.
d) Visual dashboards were made with Airtable and excel to find patterns, problems and ways to fix them.

3.4. **Duration and Sample Size**

Time Frame: February 2023 to May 2025

Data Volume:

Approximately 3000 trial leads analysed for conversion modelling
About 850 students were tracked for churn risk analysis
Over 500 parent responses coded for NPS improvement analysis

3.5. **Tools and Technology Stack**

a) CRM systems: HubSpot, CallHippo, AIsensy
b) Data Platforms: Google Sheets, Excel, Airtable
c) Communication: WhatsApp Templates, Automated follow-ups
d) Analysis: Pivot Tables, Conditional Formatting, Manual tagging for sentiment

This Method makes the research strong and useful at the same time. It makes the link between what scholars say and what business people do. The HCPCS structure is easy to understand, test and use again in future projects when real data and real customer behaviour are used.

4. **Framework Proposal**

The Human-Centered Predictive Customer Science (HCPCS) Model is a four-stage framework developed to combine behavioural intelligence, Real-Time automation and predictive analytics into customer interaction workflows. It works particularly well in high-touch, high-emotion domains such as education, where customers make decisions both logically and emotionally, unlike traditional customer analytics which focus on historical data.

HCPCS Integrates:

a) Behavioural Data (Customer Emotions, Satisfaction)
b) Interactional Data (Multi-Touch Communication)
c) Intent-Driven Metrics (Goals or Concerns Inferred)

4.1. **Theoretical Foundation**

The HCPCS Model Draws From

a) Nudge Theory (Thaler & Sunstein, 2008)
b) Customer Journey Theory (Lemon & Verhoef, 2016)
c) Predictive Analytics from CRM And Machine Learning Literature
d) Human-Centered Design Principles (IDEO, 2013)

The goal is to move beyond traditional funnel thinking and treat the customer as a dynamic, learning agent whose behaviour, needs and satisfaction evolve over time.

4.2. **Four Major Stages of HCPCS**

Stage 1: **Customer Experience Mapping & Friction Identification**

Customer experience maps keep track of all the interactions a customer has with a brand, from the first question they ask to the point where they are happy and tell others about the brands. To get the full picture of the experience ecosystem, we need to find all the touchpoints with customer across different platforms, such as the web, WhatsApp, class sessions, comments and so on.

Friction identification can occur during the customer experience by using Networked Dashboards (i.e., Airtable, CRM + Analytics Dashboards) to monitor various metrics at different stages of the customer journey i.e., drop-off rates, time to completion, low session attendance, number of support tickets - to reveal the areas where the customer experiences frustration or dissatisfaction.

Journey science combines mapping with behavioural data and is an important element in identifying the friction points along the customer experience journey. Companies using Predictive Journey Maps have been able to remove friction and optimise transition points between stages of the customer journey, resulting in a conversion improvement up to 40%.

Stage 2: **Micro-Personalization Using CRM + Feedback Loops**

This focuses on creating micro-personalized behavioural profiles of customers using CRM fields (i.e., engagement scores, tone of message, trial activities, feedback tags) to classify customers based on their level of engagement (i.e., highly engaged, uncertain, indifferent).

To further personalise communications with customers, we also establish feedback loops through Net Promoter Scores (NPS), post-class survey responses and WhatsApp reviews to guide personalised outreach initiatives. Outreaches like motivational nudges, personalised content or coaching.

We continue to refine our communication strategy based on the trend of feedback from customers. With the use of predictive CRM tools and feedback loops, we are able to personalise communications with customers at every stage of the journey

Stage 3: **Predictive Alerting Based on Behavioural Triggers**

In this third stage of the HCPCS framework, we implement churn-prediction models to alert us to early warning signs of potential churn e.g., lack of trial activity, session no-shows or negative feedback in real-time.

These models typically utilize algorithms trained on historical interaction data to predict the likelihood of a customer churning prior to the actual occurrence of the event.

Once we have identified a customer who is at risk of churning, triggers from WhatsApp or HubSpot will automatically escalate those high-risk cases to the CRM system and trigger proactive intervention (e.g., call, re-engagement messaging, etc.)

Stage 4: **Action Recommendation Engine (ARE)**

The fourth and final stage of the HCPCS framework is the Action Recommendation Engine (ARE). The purpose of the ARE is to generate action recommendation suggestions for internal teams based on the outcomes of predictions and behaviour signals. The types of actions recommended may include:

a) Scheduling callback meetings
b) Identifying opportunities for up-sells
c) Identifying follow-up opportunities for mentors
d) Providing content recommendations

4.3. Key Characteristics of the HCPCS Framework

a) Human-Centered: Focuses on the emotional and contextual aspects of the customer experience and their intentions at each stage of the journey. While automation provides support, it does not replace empathy.

b) Predictive: Uses forward-looking signals (i.e., intent indicators, sentiment, inactivity) instead of relying solely on historical data to make decisions.

c) Scalable: Designed to manage over 1,000 customers with little to no manual overhead due to the inclusion of automated predictive systems and pre-designed workflows.

d) Actionable: Reconstructs ideas into clear, role based next steps that can be taken right away and without any confusion or delay.

4.4. Applying HCPCS in Education Technology Environments

a) **Holistic Workflow Design:** Worl closely with the sales and customers experience teams to create holistic processes in the tools they already use like HubSpot, WhatsApp and Airtable. This will make it easier for everyone to start using the new framework.

b) **Real-Time Tagging**: Add WhatsApp tags to the CRM system to get feedback on how customers are feeling and what we are trying to achieve in real time. This lets the business know when someone is interested and act on that news.

c) **Integrate Feedback Databases**: Combine reviews, NPS and session ratings into a single operation database lets businesses see how customers move through the different stages of the journey.

d) **From Data to Action**: The HCPCS framework takes fragmented customer behaviours and translates them into structured triggers e.g., when sentiment levels fall or activity levels decline, the system identifies and recommends specific actions (calls, content sharing, coaching) to bridge analytical insights with empathetic responsiveness.

4.4.1. Why It Works

The four-stage HCPCS model aligns with current best practices emerging from journey science and predictive customer experience frameworks. Organisations implementing similar models have seen a double-digit increase in trial-to-conversion ratios, a reduction in churn and a tangible increase in NPS and customer lifetime value. HCPCS integrates mapping, micro-personalization, churn prediction and action automation.

5. **Case Study Analysis**

In this area, we describe two, embedded case studies that illustrate the implementation of the HCPCS model. These case studies represent operationalisations of predictive customer science in real-world, EdTech environments. The three studies each focus on a distinct business goal: lead conversion, churn reduction or NPS enhancement. They explain the problem, the solution and the results.

5.1. **Company 1 – Smart Lead Allocation and Churn Risk Model**

Company 1 trial conversion rate was about 12.5% and it was not increasing, even though they have a lot of inbound leads coming in. They did not have an automated way to allocate the leads and follow up with the right people and at the right times, so there were many high intent leads falling through the cracks.

a) Intervention: Developing a Predictive Lead Scoring System in which scoring is used for behavioural cues [12]. Company 1 developed a predictive lead scoring system using multiple behavioural cues (WhatsApp response tags, form completion quality, email open rates, and response time). The system used these cues to assign an "engagement" score to each lead. This was more than just static lead scoring because the system learned from previous success/failure patterns and adjusted the scoring accordingly.

b) Automating Follow-Up Processes: HubSpot and AISensy already had scoring logic built in, which was used to automate processes for real time leads. For leads that scored above certain levels, they were sent immediately to high-capacity counsellors. For leads that scored below levels, they were sent to nurturing workflows.

c) Ongoing Feedback Loop and Optimization: Company 1 looked over the trials every week and changed the scoring level based on what they learned and what their counsellor said. In this way, the model was always getting better and staying in sync with signs about how leads were acting.

d) Results - Real-World Performance Gains

Metric	Before	After	Change
Trial Conversion Rate	~12.5%	17.1%	+32.3% absolute increase

Time to First Counsellor Response (hours)	~2.4	~0.8	–66% decrease in response time
Counsellor Lead Quality	Baseline	Improved	22% better quality leads

Table 1. Company 1 Lead Performance Metrics Before and After Predictive Lead Scoring Implementation

This is about the same as what other companies in the same field do when they use predictive lead score to boost performance. When companies use these methods instead of the older ones, they usually see a 25-70% increase in the sales and three times a s many qualified leads.

5.1.1. **Key Findings from Practice and Literature**

a) Pattern-based scoring works better than rule-based scoring because predictive models look at how many factors are connected and find patterns that go beyond simple point rules. Because of such system we can give more accurate and flexible lead prioritization based on how signs of behaviour change over time.

b) Automation helps reduce burnout and decreases delays: By sending leads to the right counsellor at the right times, Company 1 counsellor could engage with high-intent leads in a timely manner and reduce their manual workload. [9]

c) Feedback-driven optimization ensures relevance: Because predictive scoring is continually optimized based on the evolving behaviours of customers, it has long-term performance implications, as demonstrated by best practices in lead scoring literature.

d) Increased lead quality reduces operational waste: Counsellor at Company 1 said they spent less time dealing with unqualified leads and therefore were able to spend more time on qualified leads. As seen in many other cases of predictive lead scoring, increased quality reduces waste and improves customer experience.

5.2. **Company 1 - NPS Improvement**

5.2.1. **Problem Statement**

Even though the educational performance and instructional delivery at Company 1 was high, the Net Promoter Score (NPS) remained at a relatively stable level. The parent feedback received at Company 1 was not being effectively utilized.

a) **Establishing a Voice of Parent (VoP) System:** Company 1 sets up a structured VoP system where feedback (session scores, WhatsApp comments, and NPS) was categorized and marked every week for closure, tracking or escalation. Mood and urgency were recorded using WhatsApp templates and feedback was sent straight to the operations and delivery team so that they work on it quickly.

b) **Kanban Feedback Board:** Made a visible board to show where the feedback was in the process (Open, IN-progress, closed), making sure that no feedback got lost.

c) **Targeted Escalation Workflow**: Sessions with low scores led to targeted call backs with offers to switch teachers or get more help, all based on the sentiment's tags.

d) **Motivational Culture Initiative**: We started a campaign called "5-star parent story", for motivating people. The teams were told about good comments so that they can reward good behaviour and hard work.

5.2.2. **What was Achieved in Four Months?**

Metric	Pre-Campaign	Post-Campaign	Change
NPS	51	61	+13 points; +27%
Referrals / Inquiries	Baseline	Up 22%	—
Trust Signals Sibling Enrolments	Baseline	Up 12%	More engagement

Table 2. Company 1 Net Promoter Score (NPS) and Engagement Metrics Before and After the Voice of Parent (VoP) Initiative

5.2.3. **How Did We Get There?**

a) Feedback Loop Closure: Following up with the people at the correct moment to let them know that they are heard is a big part of making them happy and getting them to come back.

b) Data → Action → Improvement: Auto and General and Ciox health indicate that NPS goes up when feedback systems lead to improvement in operations that can be made and have effects that can be measured.

c) Sentiment in Real Time as Fuel: Parents' input through WhatsApp and sessions review set off escalation triggers, just like how big businesses use AI to pick up on voice cues and make quick corrections.

d) Internal Cross-Functional Engagement & Recognition: Sharing success stories within the organization helps lift spirits and keep employees focussed on the customers, which is a good way to keep customers happy.

e) Wider Relevance: NPS as Growth Drivers shows that even a small increase in the NPS can have big effects on a business [16]. In this case, a 7- point rise in NPS usually means about

1% more sales and less customer turnover. Company 1's NPS went up by 13 points which helped them get more leads and keep more customers.

5.3. **Company 2 – Personalized Retention Roadmap**

a) **Issue Definition**: 18.2% of regular learners dropped out, which is an issue. There was a planned process for getting new students started, but after the third week, many students lost interest and quick taking part. A lot of students dropped out because the general outreach to keep them in school did not meet the needs of the different groups of students.

b) **Solution Strategy: Behavioural Segmentation Model**: The students were split into three groups based on their behaviour: active, at risk and disengaged. Tod o this, we looked at how many sessions they went to, how many assignments they turned in, and how many support tickets they started. This helped to figure out what they needed help with and how to give it to them.

c) **Implementation: Proactive Engagement Strategies:** Strategies for proactive engagement students who were at risk of dropping out got personalized messages, motivational prompts and milestone-based nudges to get them to join and get back involved before they dropped out.

d) **Dashboards to Identify Churn-Risk:** Visual dashboard showed how involved students were and teams were notified in real time when students were not doing anything or were not interested, so senior mentors could step in and help.

5.3.1. **Effects & Outcomes**

Metric	Pre-Campaign	Post-Campaign	Effectiveness
Drop Off Alerts	Baseline	–21%	Less drop-off signals
Churn Rate	18.2%	13.7%	–24.7% relative
Net Promoter Score (NPS)	Baseline	+12 pts	Satisfaction levels improved
Referral Intent	Baseline	Up	Word of mouth increased

Table 3. Company 2 Retention Performance Before and After Behavioural-Segmentation Interventions

5.3.2. **How Did We Do That?**

a) **Segmentation = Precision**: Putting students into groups based on how engaged they are lets one tailor the lessons to their specific needs based on how they behave. Several methods have been proven to work by research.

b) **Targeting = More Efficient**: When segmentation and behavioural triggers are used together, it is easier to get in touch with people, less contact is needed, and resources are put where they will have the most impact. Predictive systems have been shown to help keep customers longer in aa number of different areas.

c) **Dashboards = Timely Action:** Behavioural analytics lets teams spot disinterest early on, before it gets worse and leads to turnover. According to research in the SaaS business, using comparable can cut churn rates by large amount.

e) **Still Important = Human Interaction:** Automated triggers are helpful but adding human interaction like checking in with a mentor, has been shown to keep people interested as seen in the case studies of learning analytics.

6. Experimental Data and Visualizations

The three key KPIs that are used to measure how well the interventions work are: Lead Conversion Rate, Churn Rate and Net Promoter Score (NPS).

6.1. Company 1 Lead Conversion Performance

Month	Before Optimization (%)	After Optimization (%)
January	12.5	14.3
February	13.1	15.6
March	12.8	16.2
April	12.9	16.5
May	13.0	17.1

Table 4. Company 1 Lead Conversion rates before and after optimization (Jan - May)

The AI based routing system made r4esponses faster and helped match leads with better quality.

6.2. **Company 2 Churn Rate Analysis**

Quarter	Churn Rate Before (%)	Churn Rate After (%)
Q1	18.2	15.4
Q2	17.5	14.6
Q3	17.9	13.9
Q4	18.0	13.7

Table 5. Quarterly churn rates before and after the retention optimization campaign

Churn rates went down consistently over four quarters, for a total of 4.5% or about 25%. Behavioural nudges and dashboards that let teachers know when the students were not paying attention were two important factors that made this work.

6.3. **NPS Growth and Engagement Trends**

Month	NPS Before	NPS After
February	48	54
March	49	56
April	50	59
May	51	61

Table 6. Monthly NPS improvement following implementation of sentiment-driven feedback workflows

NPS went up by 13 points in four months. A systematic feedback loop and escalation mechanism made it possible for parent's complaints to be heard, dealt with and followed up on, which led to more satisfied parents and more referrals.

6.4. **KPI Summary Table**

Metric	Pre-Intervention	Post-Intervention	Change (%)
Conversion Rate	12.5%	17.1%	+32.3%
Churn Rate	18.2%	13.7%	–24.7%
NPS Score	48	61	+27% (pt gain)
Average Response Time (hours)	2.4	0.8	–66.6%

Table 7. Summary of Pre- and Post-Intervention KPIs across all two case studies

These real-world findings show that combining predictive modelling with CRM processes and behaviour-based customer engagement works well. Also, these results show that the HCPCS model is a method they can be used again to get real business results.

7. **Implications and Future Scope**

The HCPCS framework affects more than just the teach business for schools. It also affects a lot of other fields where people associate with each other a lot, where connections are valuable and where emotions run deep. Even though this study was mostly about teaching technology, the model and its ideas can be used in many other fields as well.

7.1. **Industry-wide Transferability**

The HCPCS model can be used in several fields, including:

a) Healthcare

* Predictive patient engagement
* Appointment adherence
* Emotional nudges

b) Financial Services

* Risk profiling
* Satisfaction recovery
* Upsell readiness modelling

c) E-commerce

* Dynamic product recommendations

* Cart abandonment intervention

d) Telecommunications

* Proactive churn alerts
* Usage-based personalization

All these industries work with large amounts of customer data, which would also be benefited by using human centric modelling.

7.2. **Opportunities For Technological Advancement**

Improvements in artificial intelligence and customer experience analytics in the future will make the HCPCS system more complete by including:

a) Emotion AI and Voice Analytics
b) Tone and emotion analysis in real time through chat and phone calls.
c) Digital twin of the customer
d) Maing virtual models of how customers act so that interventions can run through them and tested
e) No-code CRM integration platforms
f) making it easier for anyone to use forecasting models without knowing how to code
g) API-based personalization engines

7.3. **Academic Research and Development**

Customer science is still new, so we need to learn lot about it. Researchers can now make some simple rules for how to measure how happy and how often a customer leaves. They can also do tests to see if nudges and feedback loops help. Plus, they can study how people from different places and cultures react to personalization.

7.4. **Policy and Ethical Governance**

As the level of personalization increases, so will the regulatory interest. Academic research should remain aligned with changing policies related to AI ethics, algorithmic transparency. Institutions need to prepare for regulatory scrutiny of algorithmically driven decision making by requiring assessments of the impacts of customer models that utilize AI new consent in real-time personalization scenarios.

8. **Limits**

Although the HCPCS framework showed benefits in all three metrics (Conversion, Retention, and Satisfaction), there were limits to the study and these limits should be noted to place the results in context and to point out how they could be improved.

8.1. **Limitations related to the sample and its context**

The study was carried out in the context of EdTech platforms, primarily focusing on parent-child decision makers who use digital education. The cultural, emotional, and financial variables present in this type of industry are unlikely to be applicable to other types of industries, such as B2B SaaS or health care. All data collected came from companies that have medium-to-high levels of CRM and technical maturity, low-technology companies will likely have barriers to integrating HCPCS.

8.2. **Time-related constraints**

The observation period (February 2023 to May 2025) included less than two complete academic periods. There may have been seasonal variations in user behaviour during school vacations and examination periods, and these may have occurred unpredictably.

8.3. **Tool and platform dependence**

The framework relies extensively on tools such as HubSpot, AISensy, and WhatsApp.
Smaller businesses that have limited automation capabilities may find it difficult to implement HCPCS without having access to no-code tools.

8.4. **Risks related to measurement and interpretation**

a) NPS is relative, so it doesn't always show how loyal customers are to a company or how much they value or what the company offers.

b) Sometime sentiments tagging had to be done by hand, which made the sentiment classification process mor likely to be biased.

c) Most of the interactions with the users were digital like opening rates, tags or clicks. There were no offline interactions or minor cues from the environment.

9. **Conclusion**

This dissertation looked at Customer science from both theory and empirical point of view. Behavioural economics, customer journey designs and predictive analytics have all been brought together to create a strong and scalable model for increasing lead conversion, customer retention and happiness.

With all most ten years of real world experience this research goes beyond theory and backs it up with EdTech case studies, when processes with AI, feedback loops and CRM automation were used together, conversion rates went up. This shows that customer science can work in the real world when combined with empathy, technology and focus.

The HCPCS structure is more than just a way to do things. It is a way of thinking about business that puts the customer at the centre of data flows, teamwork and smart decision. The model can only be used in certain ways but because it is flexible, it can be changed to fit the needs of different businesses.

In the end, this paper makes the case for a future in which companies do not just serve customers but also change, to fit their current actions, emotions and requirements.

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