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EVALUATION OF THE EFFECTIVENESS OF MARKETING CAMPAIGNS IN BANK DIGITAL CHANNELS: ATTRIBUTION METHODS, A/B TESTING, UPLIFT MODELING

Zdorovyi Maksym Pavlovych[1]
Scientific supervisor: Horokh Oleksandr Volodymyrovych[2]

1. Postgraduate Student
State Biotechnological University, UKRAINE
ORCID ID: 0009-0008-6904-0007

2. PhD (Economics), Associate Professor,
Associate Professor of the Department of Finance, Banking and Insurance
State Biotechnological University, UKRAINE

In the digital era, retail banks increasingly rely on online channels to market products and engage customers. Whether promoting a new credit card, encouraging loan applications, or onboarding users to a mobile banking app, banks invest heavily in digital marketing campaigns. Measuring the effectiveness of these campaigns is crucial to ensure marketing spend yields a strong return on investment (ROI) and to refine strategies in a competitive financial services landscape. Banks have the advantage of extensive customer data – nearly every product signup or service usage is accompanied by rich data points due to the personal information exchanged during banking processes. This data can theoretically enable detailed tracking of a customer's lifecycle and interactions. In practice, however, financial marketers often find it challenging to accurately measure performance across the complex, multi-step customer journeys common in banking. Consumers might encounter a bank's brand through multiple touchpoints – for example, seeing a social media ad, reading an email newsletter, clicking a paid search link, and visiting the website directly – before eventually converting to a product. Traditional tracking may give undue credit to the last step or struggle to attribute outcomes to earlier touches, leaving teams unsure which channels or campaigns truly drive new customer acquisition. Modern measurement is nuanced and demands not only clean data but also sophisticated analytical methods.

Attribution Methods in Digital Banking Campaigns:

1) Concept and Importance. Marketing attribution models are designed to allocate credit for conversions (such as account openings, loan applications, product sign-ups) to the various marketing touchpoints that a customer encountered along their journey. Rather than simply crediting the last interaction that immediately precedes a conversion, attribution analysis recognizes that consumers often engage multiple times through different channels before making a decision. For example, a prospective customer might first learn about a bank's new credit card via a Facebook ad, later search for the card on Google and click a search ad, and eventually sign up after receiving an email offer. Attribution methods help banks understand these omnichannel campaigns by assigning appropriate weight to each interaction, instead of only the final step that "closed" the conversion. This is especially pertinent in banking, where research and consideration phases can be long – a customer rarely opens a new bank account or loan on the very first website visit. By using attribution modeling, banks gain insights into which channels and marketing activities are contributing at each stage of the funnel, informing more effective budget allocation and channel strategy.

2) Single-Touch vs. Multi-Touch Models. Early or simplistic approaches often use single-touch attribution, wherein a single touchpoint receives 100% of the credit for the conversion. Common single-touch models include last-click attribution, which credits the last marketing interaction (e.g. the last clicked ad or link before conversion), and first-click attribution, which credits the first interaction that initiated the customer's journey. Banks historically may have relied on last-click models (for instance, giving full credit to the last email or ad that led a customer to sign up) due to their simplicity and the default settings of many advertising platforms. However, single-touch models provide a narrow view and can be misleading in a world where the "modern customer often takes hundreds of steps in their journey" and interacts with multiple brands and channels. In contrast, multi-touch attribution models distribute credit across multiple touchpoints. There are rule-based multi-touch models (such as linear attribution that gives equal credit to all touches, or time-decay that gives more credit to later touches) and more advanced algorithmic models that use data-driven algorithms to assign fractional credit to each interaction based on its influence. For example, Google's data-driven attribution uses machine learning on conversion data to determine how much each ad or keyword contributes to the outcome. Multi-touch attribution aims to eliminate bias and capture the real contribution of each channel

in guiding the customer, which is crucial for banks running omnichannel campaigns where paid search, display ads, email, social media, and direct website visits might all play a role in a single conversion path.

3) Application in Banking and Case Example. Implementing attribution modeling in a banking context allows marketers to answer questions like: Which marketing channels are most effective in acquiring new checking account customers? What combination of touches tends to precede a mortgage application? One practical example is Cetelem, a European consumer finance bank (part of BNP Paribas), which sought to move beyond last-click attribution to a more comprehensive view of the customer journey for online loan applications. In a recent project, Cetelem's team conducted a journey-based campaign analysis with extended attribution modeling. They audited and supplemented their analytics data to capture full conversion paths and compared different attribution models. The result was the development of a custom multi-touch attribution model tailored to the personal loan journey, replacing the simplistic last-click approach they had used before. This analysis revealed valuable insights, such as the need to consider longer look-back windows (many customers took longer to convert than previously assumed) and identification of certain marketing channels that were bringing in lower-quality leads (for example, some sources correlated with higher credit risk among applicants). By defining the role of each channel at each stage of the funnel, the bank could clearly see if any channel was previously over- or undervalued in its impact on conversions. With the new attribution model in place, campaign spend could be adjusted more optimally – for instance, increasing investment in channels that assist early in the decision process but weren't getting credit under a last-click model. This case demonstrates how attribution modeling in a bank's digital marketing can lead to a 360-degree view of the customer journey, enabling data-driven decisions on where to focus marketing resources for maximum effectiveness. Overall, attribution methods form a foundational tool for evaluating marketing in digital banking. They provide a retrospective analysis of how various channels and touchpoints work together to generate outcomes. By moving to multi-touch and data-driven attribution models, banks gain a more accurate understanding of marketing ROI across channels. In practice, many banks leverage built-in attribution reports from platforms like Google Analytics 4 or advertising tools, which can show assisted conversions and path analysis, and some develop custom models for deeper insight. The insights from attribution modeling guide marketers in planning future campaigns – for example, identifying that display ads primarily assist awareness (early funnel) while search ads drive last-step conversions, or that certain sequences of touches are particularly effective. This ensures marketing efforts and budgets are aligned with the channels that truly influence customer acquisition and conversion in the digital space.

A/B Testing for Campaign Optimization:

1) Principles of A/B Testing. While attribution analysis deals with assigning credit in observational data, A/B testing (or split testing) is an experimental method to directly measure the causal impact of changes in marketing campaigns. In an A/B test, the idea is to create two (or more) variants of a marketing element – such as an advertisement, webpage, email, or mobile app screen – and randomly split the audience so that one group sees variant A (often a "control" or current version) and another group sees variant B (the "test" version). By controlling for other factors and ensuring the groups are statistically comparable, any significant difference in outcomes (e.g. click-through rates, conversion rates, revenue) can be attributed to the variation in that element. Formally, A/B testing is essentially an experiment where users are randomly assigned to different versions and statistical analysis is used to determine which version performs better for a defined goal. This method is widely regarded as a gold standard for establishing causality in marketing: it answers questions like "Did the new campaign design actually increase conversions, or would those customers have converted anyway?"

2) Use in Digital Channels. In digital banking channels, A/B testing is both feasible and valuable because interactions are online and outcomes can be tracked in real-time. Banks employ A/B tests to optimize websites and apps (for example, testing two versions of a home page or a loan application form), to refine digital ads (testing different headlines or visuals), and to improve communications (comparing two email subject lines or two push notification messages). A key best practice is to test one change at a time per experiment to isolate its effect – for instance, only changing the call-to-action phrasing in an online ad while keeping other elements constant. Another essential practice is to run the test concurrently for both variants under similar conditions; timing can influence user behavior, so showing version A one month and version B the next could confound the results with seasonal effects. By running both versions simultaneously and ensuring a large enough sample size and duration, banks can gain statistically robust results on which variant is superior.

3) Examples in Banking Context. Banks have reported significant improvements by applying A/B testing to their digital marketing efforts. For instance, consider a scenario inspired by a credit card marketing campaign: a large consumer bank launched an online campaign to encourage credit card applications and decided to A/B test the landing page design. The control version was a standard text-based page with information and an application form, while the test version included an embedded promotional video and a more graphical layout. By splitting incoming visitors between the two versions, the bank could directly measure which page led to a higher rate of completed applications. Such

an experiment might reveal, for example, that the video-enhanced page increased conversion by a certain percentage, providing clear evidence to adopt that design for all users. In another real case, Penn Community Bank (a regional bank in Pennsylvania) integrated A/B testing as a continual part of its marketing optimization. The bank's Chief Experience Officer noted that they "actively leverage A/B testing and other modes of evaluation to assess our campaigns and measure performance in an increasingly crowded financial services market". This practice of continuous testing helped the bank refine various campaign elements over time – for example, after an initial direct mail offer, they tested adding an incentive and found that increasing a sign-up bonus from $250 to $350 improved response rates in subsequent waves. A/B testing is not limited to visual design or copy changes; it can also test marketing strategy variations. A notable example is testing channel mix. Penn Community Bank experimented with adding an email touch to a traditional direct mail campaign to see if it would increase overall engagement. They split their prospect list so that one group received only the physical mailer, while another group received the same mailer plus a follow-up email. The results were telling: the combined email+direct mail group saw an average lift of about 26% higher response compared to the direct-mail-only group. This kind of controlled test allowed the bank to quantify the incremental benefit of an additional channel. Encouraged by the result, they planned further experiments adding digital advertising as another variant, to measure the contribution of each channel to the campaign's success in terms of ROI. These examples illustrate how A/B tests in banking can validate ideas (e.g. "does adding an email reminder increase conversions?") with concrete data.

4) Benefits and Considerations. The advantage of A/B testing is its clarity – by observing outcomes from randomized test and control groups, banks get unambiguous evidence of a marketing change's effectiveness. This reduces reliance on guesswork or correlations and can challenge assumptions. However, there are practical considerations: sufficient sample size is needed (especially for small improvements, the test might need thousands of observations to detect a statistically significant difference), and one must ensure the test is run long enough to account for any variability over time. Moreover, in highly regulated environments, banks must ensure that no customer segment is unfairly disadvantaged by experiments (e.g. if testing an offer, often everyone who didn't receive it in the test might get a chance later so as not to withhold benefits unjustly). When designed and executed properly, A/B testing becomes a powerful tool for continuous improvement in marketing. Many digital-first banks and fintech companies have embraced a culture of "test and learn," where virtually every aspect of the customer funnel is subject to ongoing experimentation – from the wording on app store

pages to the layout of online banking dashboards – all aimed at boosting user engagement and conversion metrics. For more traditional retail banks moving into digital channels, building this experimentation capability allows them to iterate marketing campaigns based on evidence, ultimately leading to more effective campaigns and better customer experiences.

Uplift Modeling for Incremental Impact:

1) Concept of Uplift Modeling. While attribution models and A/B tests can tell us about channel contributions and what changes work best on average, uplift modeling (also known as net lift or incremental response modeling) goes a step further by predicting the individual-level impact of a marketing action. The core idea of uplift modeling is to estimate the change in probability of a desired outcome (such as product purchase or account signup) that is caused by a marketing intervention, typically by contrasting it with a hypothetical scenario of no intervention. In other words, instead of simply predicting who is likely to respond to a campaign, uplift modeling predicts who is likely to respond because of the campaign. This relies on causal inference principles: mathematically, uplift is often defined as the difference between two conditional probabilities – the probability of conversion if the customer is targeted versus if the customer is not targeted. To model this, one generally needs data from controlled experiments or randomized trial designs (at least in historical data) where a subset of customers served as a control group not receiving the marketing, so the model can learn the differential outcome.

2) Advantages Over Traditional Targeting. In traditional direct marketing common in banks (for example, sending a promotion to a list of customers), a predictive model might rank customers by their likelihood to respond. However, that model would tend to prioritize people who look likely to buy the product – which includes those who would purchase even without any marketing prompt ("sure things"), as well as those who might buy only if prompted ("persuadables"). Uplift modeling aims to specifically target the persuadable segment – those who have a low likelihood of acting on their own but a high likelihood of acting if influenced by marketing. Simultaneously, it can identify and exclude two other groups: the "sure things" who will buy anyway (thus wasting marketing spend on them yields no incremental gain) and the "lost causes" who will not respond even with encouragement. A further group often considered is the "do-not-disturbs," customers who might react negatively to the marketing (for instance, getting annoyed by an unsolicited offer and potentially reducing their engagement). By targeting only those who are positively influenced by the campaign, uplift modeling allows banks to optimize targeting to maximize incremental ROI – achieving the same or greater results with less marketing cost and less risk of alienating customers.

3) Dramatic Improvements in Campaign Performance. Several banks have reported remarkable success by applying uplift modeling to their campaigns, especially in areas like cross-selling to existing customers or retention marketing. A well-known case is a large retail bank in the United States (not named for confidentiality) that applied uplift modeling when marketing a new high-margin banking product. Instead of mailing their entire customer base, they used an uplift model to mail only those customers predicted to be positively influenced by the offer. The outcome was an increase in sales by about 10% while mailing 60% fewer customers, which in effect more than doubled the profitability of the campaign compared to the previous approach. The uplift model achieved almost the same number of new product sign-ups as a mass mailing would, but at a dramatically lower cost, and with far less waste. In addition to cost savings, avoiding mailing uninterested customers can improve customer experience by reducing irrelevant communications. Another example comes from U.S. Bank's Consumer Direct division, which implemented uplift modeling for their home equity loan cross-sell campaigns. After deploying an advanced uplift modeling solution, U.S. Bank saw over a 300% increase in incremental cross-sell revenue for those campaigns, amounting to over $1 million in additional revenue from just two campaigns, and achieved this with approximately 40% reduction in mailing volume per campaign. In one specific credit line offer, incremental responses (responses attributable solely to the marketing) rose 189% year-over-year once they optimized targeting through uplift modeling. These figures underscore how effective targeting of only the right customers can vastly improve both the top-line and bottom-line impact of marketing efforts. Uplift modeling not only boosts immediate campaign metrics but also yields longer-term benefits. By reducing contacts to only those necessary, banks can lower the risk of contact fatigue among customers and avoid the negative effects of over-communication. Moreover, analyzing uplift can enhance organizational understanding of what works in marketing. For instance, seeing which customer segments have high uplift in response to a given offer can inform product strategy and messaging (perhaps certain demographics or behaviors indicate a truly persuadable audience). Some key benefits of uplift modeling for demand generation and customer retention campaigns include:

- Higher ROI and lower cost;
- Reduced customer irritation: Minimize unnecessary or unwanted solicitations;
- Improved insight into campaign effectiveness;
- Better customer retention.

4) Implementation Considerations. To employ uplift modeling, banks require robust experimental data and modeling capabilities. Typically, a random control

group is set aside in campaigns to collect unbiased data on how customers behave without contact, which is then compared to similar customers who were contacted. Advanced machine learning techniques, including decision trees or newer approaches like causal forests and meta-learners, can be used to train uplift models that output an uplift score for each customer (the predicted increase in probability of conversion if targeted). Banks like U.S. Bank initially tried in-house "uplift-like" models but found them hard to maintain; they eventually adopted dedicated uplift modeling software that automated model refresh and validation. The success at U.S. Bank led them to extend uplift modeling to multiple product lines, after seeing consistent improvements in return on marketing investment (ROMI) across the board. Today, uplift modeling is increasingly part of the toolkit in data-driven marketing organizations. Some of the world's top financial firms have used uplift modeling solutions to enhance campaign targeting, and with the growing emphasis on personalization and AI in marketing, the technique aligns well with the goal of treating customers individually based on their likely response to interventions.

Synthesis of Approaches in Practice. Each of the three methods discussed – attribution modeling, A/B testing, and uplift modeling – addresses marketing effectiveness from a different angle, and they are often complementary when used together. In a comprehensive marketing analytics strategy, attribution analysis provides a broad view of how various channels contribute to conversion outcomes, A/B testing provides localized but highly reliable evidence on what works best in specific situations, and uplift modeling provides a predictive, targeting-focused approach to maximize incremental gains. Forward-thinking banks integrate all three to create a robust feedback loop for continuous improvement. For example, attribution modeling might reveal that a bank's mobile app advertising is driving a lot of initial account sign-ups, but that many customers also respond after an email follow-up – indicating a synergy between channels. Based on this, the bank could plan an A/B test to experiment with the timing or content of the follow-up email to see if it can boost conversion rates for those who initially showed interest via the app. Once the best-performing approach is identified by the A/B test (say, a certain email subject line or sending the email within 24 hours of app install), the bank can implement that change for all customers. Then, to further refine the campaign, they could use uplift modeling on the next wave – targeting only those users who wouldn't convert without the email, as opposed to blasting everyone who installed the app. In this way, attribution guides strategy by highlighting multi-channel effects, A/B testing optimizes the tactics, and uplift modeling sharpens the targeting to ensure marketing efforts are truly effective and efficient. Banks that have successfully adopted these methods also emphasize the importance of measurement culture and data infrastructure. It's vital to define clear Key Performance Indicators (KPIs) and success metrics for campaigns. Many banks now track not just raw response rates, but lift (incremental impact measured against a control) and ROMI (return on marketing investment) as critical metrics. For instance, Penn Community Bank, in partnership with analytics consultants, established benchmarks such as "lift over control, incremental accounts, and account profitability" to evaluate their checking account acquisition program. By analyzing lift, they could see the true added value of their marketing, filtering out background customer behavior. This kind of rigorous approach, supported by proper data collection and analysis, enables continuous learning. After each campaign or test, the insights feed back into the next cycle of planning. Over time, this leads to significantly improved marketing performance: as seen, for example, in how Penn Community Bank increased the frequency of its outreach (from biannual to quarterly) once it gained confidence in a highly targeted, data-optimized approach that consistently delivered measurable results.

Conclusion. Evaluating the effectiveness of marketing campaigns in banks' digital channels requires a combination of rich data, analytical techniques, and a willingness to test assumptions. Attribution models, A/B testing, and uplift modeling each contribute a vital piece to the puzzle of understanding and improving marketing outcomes. Attribution methods allow banks to look holistically at customer journeys and assign proper credit to marketing touchpoints, ensuring that no channel's contribution is overlooked in an omnichannel environment. A/B testing brings scientific rigor to marketing by enabling banks to isolate and prove what actually works, thereby optimizing campaign elements and customer experiences based on evidence. Uplift modeling brings in the power of predictive analytics and causal inference to focus resources where they matter most, boosting campaign ROI and reducing waste through intelligent targeting. The interplay of theory and practice is evident – these methods are grounded in disciplines like statistics, econometrics, and machine learning, but their value is ultimately demonstrated in real business results. The case studies discussed show that banks embracing a data-driven approach have achieved substantial improvements: higher conversion rates, greater incremental sales, lower marketing costs, and better customer engagement. In retail banking, where margins can be thin and competition is fierce (including from digital-only fintech startups), the ability to accurately measure and enhance marketing effectiveness is a significant competitive advantage. By combining attribution analysis to guide strategy, A/B testing to refine tactics, and uplift modeling to maximize incremental impact, banks can create a virtuous cycle of marketing optimization. As digital channels continue to evolve – with new platforms, privacy considerations, and AI-driven personalization – the foundational need for robust campaign evaluation will only grow. Banks that build strong capabilities in these areas will be well-positioned to adapt and thrive, delivering the right message to the right customer at the right time, and confidently knowing the value each campaign delivers. References:

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