Articles

Economics of cold emailing

La economía del correo electrónico frío

Stevens Reyes-Simpe*
Daria Kubantseva*

ABSTRACT
This study provides a mathematical model that analyze the factors that determines response rates in bulk cold emails. To test the model, we conducted an empirical analysis based on data from our experiment that included 5,187 cold emails, having an average response rate of 15%. Three key determinants were found: email length combined with the sender's presentation timing, personalization for non-patient buyers, and the time between each product's features presentation. Specifically, the findings claim that an email under 150 words with a timing introduction of the sender (up to 3 seconds after the start) increases the response rate from 17% to 44%. Personalization, defined as name, company, and location, for non-patient buyers increases the rate to 58%. In contrast, response rate decreases by 17% each increment of 1 second on the average time taken between presenting each product's features. Unexpectedly, some variables like price discrimination turned out to not have statistical significance on response rates.

Keywords: Cold emails, email lengthiness, personalization, sales strategy

RESUMEN
Este estudio proporciona un modelo matemático que analiza los factores que determinan las tasas de respuesta en los correos electrónicos masivos no solicitados. Para probar el modelo, realizamos un análisis empírico basado

JOURNAL OF BUSINESS and entrepreneurial studies
ISSN: 2576-0971

Journal of Business and entrepreneurial
July - September Vol. 9 - 3 - 2025
http://journalbusinesses.com/index.php/revista
e-ISSN: 2576-0971
journalbusinessentrepreneurial@gmail.com
Receipt: 16 March 2025
Approval: 09 April 2025
Page 37-47

* Master, School of Economics, Peking University PHBS Email: reyessimpe@gmail.com
https://orcid.org/0000-0002-1131-1061

* Master School of Management, Peking University PHBS kubantsevad@gmail.com
https://orcid.org/0000-0002-9777-2255

en datos de nuestro experimento, que incluyó 5187 correos electrónicos no solicitados, con una tasa de respuesta promedio del 15 %. Se identificaron tres factores determinantes: la longitud del correo electrónico combinada con el momento en que se presenta el remitente, la personalización para compradores que no son pacientes y el tiempo transcurrido entre la presentación de las características de cada producto. En concreto, los resultados indican que un correo electrónico de menos de 150 palabras con una presentación del remitente en el momento adecuado (hasta 3 segundos después del inicio) aumenta la tasa de respuesta del 17 % al 44 %. La personalización, definida como el nombre, la empresa y la ubicación, para los compradores que no son pacientes aumenta la tasa al 58 %. Por el contrario, la tasa de respuesta disminuye un 17 % por cada segundo adicional en el tiempo medio transcurrido entre la presentación de las características de cada producto. Inesperadamente, algunas variables como la discriminación de precios resultaron no tener significación estadística en las tasas de respuesta.

Palabras clave: Correos electrónicos en frío, longitud de los correos electrónicos, personalización, estrategia de ventas

INTRODUCTION

Emailing is one of the most important channels to acquire potential buyers. Aufreiter et al. (2014) stated in 2014 that email channel will keep being useful since it serves as a primary and effective mean of communication between sales representatives and potential customers, which can be observed nowadays, due to salespeople dedicate approximately 21% of their working hours to the task of just writing and sending emails (Suresh, 2023). In addition, some marketing studies strongly suggest that 80% of buyers keep indicating their preference for being contacted through cold emails, which makes sense in the big picture when comparing a leading 43% of salespeople that rate it as their most effective sales channel (Suresh, 2023). However, aside the potential suggested, cold emailing faces significant challenges when it comes to response rates. Gartner (2019) found that only 23.9% of cold emails are opened, with just an 8.5% of recipients eventually replying to the messages (Dean, 2019).

These data suggest a gap between the perceived effectiveness of cold emailing as a sales channel and its per-email performance. This gap is largely driven by the many variables that influence the success rate of cold emails, including factors such as personalization, subject lines, and list segmentation, specifically, research suggests that personalization increase the response rate of cold emails up to 32.7% compared to non-personalized emails (Dean, 2019). Moreover, subject lines that state a question have been shown to increase response rates by 21%, according to Keohane (2021). Similarly, Siewierska (2024) demonstrated that reducing the number of emails recipients in each email bulk by fivefold can lead to a 60% increase in average response rates. These researches suggest the need of following some techniques in order to have higher response rates, providing some sort of recipe behind the logic of cold emails.

However, the cold email field remains under-researched under an academic scope, as Tucker (2016) argued in the Harvard Business Review. Among the few researches that used experiments, we can find Le Plaisir (2024) experiment that suggests that a lack of personalization decrease the open rate from 62.2% to 17%, and reduce the response rate from 8.9% to 0.4%. The lack of substantial academic research into cold emailing should raise some concerns, since there is a lot of strategies suggested on the internet that can be detrimental to the optimization of cold emailing. For example, during the internship of one of the authors at a Chinese company, it was witnessed how some salesmen incorporated emojis into their cold emails, inspired by internet blogs mentioning the "science" behind using emojis to enhance response rates (Collis, 2020). However, instead of increasing the response rate, it provoked many serious buyers to reply negatively, complaining that the use of emojis was inappropriate in a business context.

In this research, we aim to address this gap by developing a mathematical model for cold emailing, built upon insights from both qualitative studies, specially of Rodrigues (2024) and Tucker (2016), and real data from an experiment conducted. This experiment involved sending 5,187 emails across 32 bulk emails, each with different characteristics. By analyzing the results, we aim to empirically test our model and provide evidence-based conclusions on how to improve cold email effectiveness.

MATERIALS AND METHODS

Incentives of sending bulk cold emails

A product x is standardly priced $p(x_f)$ subject to the stage f it faces at time t, where $p(x_f) \geqslant c(x)$, so at any f there is non-negative revenue. The price curve $p(x_f)$ satisfies $\frac{dp}{dx_f} \leq 0$ and $\frac{d^2p}{d^2x_f} \geq 0$, where at $\lim_{r(x_f)\to\varepsilon} r(x_f) = p(x_f) - c(x)$, product x is transformed to $\tilde{x}$, therefore no company will face $r(x) < 0$. However, since a company wants $r(x_f) \gg \varepsilon$, then human resources will be allocated to keep sales curve at $\frac{S}{1+e^{-r(t-t_p)}}$, in which S is the maximal potential market size, r is the average growth rate, and t_p is the peak.

Since buyers b are classified into G cohorts, the standard price $p(x_f)$ can be modified by a discount subject to the seller's criteria. Therefore, a seller s sells x for P price at t, where the standard price $p(x_f)$ is multiplied by a discount $d(G)e^w$, which is a fixed discount percentage targeted to G multiplied by the factor e^w, that captures the willingness w of buyer b inferred by s. Here, seller s must satisfy that P is greater or equal to $c(x)$, or

$$\frac{\max(d(G))e^{\max(w)}}{1-\max(d(G))e^{\max(w)}}(p(x_f)-c(x)) < c(x), \tag{1}$$

to prevent $r(x) < 0$. Assuming that seller receives v percentage from $P(x_f) - c(x)$ and his sales channel is via bulk cold emails, we characterize the following three properties of it:

1. $\exists w\,[d(w) \wedge \exists q\,[e(w,q) \wedge n \subseteq q]]$, there exists a web directory $d(w)$ where q emails $e(w,q)$ are listed, from which set n of emails, that is a subset of q, is targeted.
2. $\forall b \in B\,(\exists g \in G\,(b \in g))$, for every buyer b in the set B there exist at least one cohort g in G set[*] such that b is an element of g.
3. $\exists \beta\,(m(x,\beta) \wedge \beta \cap q \neq \emptyset \wedge (b \in \beta \wedge b \in n))$, there exists a set β such that product x is marketed to $m(x,\beta)$, which intersects with the set q (then β contains some potential clients from q). Thus, b could be member of both set β and n.

Under these properties, we can satisfy that if $N < \dot{N}$ then $r(N) < r(\dot{N})$ for $n_1, n_2 \in N$, where $r(N)$ is response. However, $\frac{r(N)}{N}$ not necessarily increases. Therefore, $\lim_{N\to\infty} \frac{s(N)}{N} > 0$ entails that while more bulk emails are sent the total sales will always increase since $\rho_{r(\cdot)s(\cdot)} \neq 0$. Thus seller s has the incentive to gradually send more N emails, since ω clients can be get and $\omega v(P(x_f) - c(x))$ commission.

Presenting oneself, personalization, and email lengthiness

Seller s writes an email $\tilde{e}$ of y words and decides to introduce himself after $\check{z}$ seconds from the beginning of the email. Now, consider that buyer b can be classified in a 2x2 F features matrix: potential (θ) vs non-potential ($\neg\theta$) and patient (τ) vs non-patient ($\neg\tau$).

We can infer $\rho_{FG} \neq 0$ exist, since if we classify consumers for their income, there is a higher chance that higher income consumers will be more potential to buy x than those from a lower income cohort. However, we will relax that assumption to the minimum for our model.

Assume that each b has a threshold of $\bar{z}$ seconds to stop reading the email. Therefore, we can arrange their threshold of seconds as follow: $\bar{z}_{\theta\tau} \geq \bar{z}_{\neg\theta\tau} > \bar{z}_{\theta\neg\tau} > \bar{z}_{\neg\theta\neg\tau}$. If s introduce himself at $\check{z}$ and its not within its respective threshold, then b will not respond $\tilde{e}$, so $r_b(\tilde{e}) = 0$.

If $\check{z} < \bar{z}$, now to increase the probabilities of a $r_b(\tilde{e}) = 1$, we consider that b takes a minimum time to dimension the lengthiness y of the email $\tilde{e}$. We assume a threshold for lengthiness $\bar{y}$, with the following arrangement among buyers $\bar{y}_{\theta\tau} \geq \bar{y}_{\neg\theta\tau} > \bar{y}_{\theta\neg\tau} > \bar{y}_{\neg\theta\neg\tau}$, therefore,

---

[*] The set G can be classification of different features (sex, age, nationality, etc.).

Proposition 1. To have non-zero probabilities of receiving a response $p(r_b(\tilde{e}))$, $\tilde{e}$ follows $p(r_b(\tilde{e})) \neq 0 \wedge (p(r_b(\tilde{e})) = 1 \text{ or } p(r_b(\tilde{e})) \neq 1) \Leftrightarrow (\check{z} \leq \bar{z}) \wedge (y \leq \bar{y})$.
In addition, we can consider that in some degree personalization can help to increase $p(r_b(\tilde{e}))$, therefore, s can choose personalizing $\tilde{e}$ subject to β characteristics $\beta \ni \{\text{name, company, location, } \dots\}$. If b is non-potential $\neg\theta$, then, under $\beta_1 > \beta_2$, where $\tilde{e}(\beta_1) > \tilde{e}(\beta_2)$, we will have $p(r_b(\tilde{e}(\beta_1))) \approx p(r_b(\tilde{e}(\beta_2)))$, however, if b is θ, then $p(r_{\theta\tau}(\tilde{e}(\beta_1))) \geqslant p(r_{\theta\tau}(\tilde{e}(\beta_2)))$, meaning that an ε exists in the differences, therefore, $\mathbb{E}[\omega v(P(x_f) - c(x)) \mid \tilde{e}(\beta_1)] > \mathbb{E}[\omega v(P(x_f) - c(x)) \mid \tilde{e}(\beta_2)]$, creating incentives to personalize more the email but bounded to $\bar{y}$.
Proposition 2. Personalization increases probabilities of a response if $b \in \theta$ with constant differences depending on τ.

Time-subject features presentation

Product x has a set φ of features, if b is from the non-potential cohort $\neg\theta$, then, under $\varphi_1 > \varphi_2$, where $\tilde{e}(\varphi_1) > \tilde{e}(\varphi_2)$, we will observe $p(r_b(\tilde{e}(\varphi_{1,2}))) \neq 0 \wedge \vartheta$, where $|\vartheta - 0| < |\vartheta - 1|$ and $p(r_b(\tilde{e}(\varphi_1))) \approx p(r_b(\tilde{e}(\varphi_2)))$. However, if $b \in \theta$, then, if $\tilde{e}(\varphi_1) > \tilde{e}(\varphi_2)$, so $p(r_b(\tilde{e}(\varphi_{1,2}))) \neq 0 \wedge \dot{\vartheta}$, where $|\dot{\vartheta} - 0| > |\dot{\vartheta} - 1|$ and $p(r_b(\tilde{e}(\varphi_1))) > p(r_b(\tilde{e}(\varphi_2)))$.
However, delivering the φ features to b in $\tilde{e}$ is always bounded by $\bar{y}$ and

$$\mu(\varphi) = \frac{1}{n-1}\sum_{i=1}^{n-1}(\varphi_{i+1} - \varphi_i)\,, i \neq \emptyset \text{ and } \exists x, y \in i \text{ such that } x \neq y, \tag{2}$$

where $\mu(\varphi)$ is the average time between presenting one feature from another in the email. Since we face potential patient ($\theta\tau$) vs non-patient ($\theta\neg\tau$) client, then $\theta\tau$ client under $\mu(\varphi_1) > \mu(\varphi_2)$, where $\varphi_1 \approx \varphi_2$, will have the following probability $p(r_{\theta\tau}(\tilde{e}(\varphi_1))) \sim p(r_{\theta\tau}(\tilde{e}(\varphi_2)))$. In contrary, when client is $\theta\neg\tau$, under $\mu(\varphi_1) > \mu(\varphi_2)$, where $\varphi_1 \approx \varphi_2$, he will have $p(r_{\theta\tau}(\tilde{e}(\varphi_1))) < p(r_{\theta\tau}(\tilde{e}(\varphi_2)))$.
Proposition 3. Probabilities of a response increases for $b \in \theta, \neg\tau$ when s minimizes the average time between features' presentation $\min_{\mu(\varphi)} \mu(\varphi) = \frac{1}{n-1}\sum_{i=1}^{n-1}(\varphi_{i+1} - \varphi_i)$.

Pricing

S prices x bounded by $\frac{\max(d(G))e^{\max(w)}}{1-\max(d(G))e^{\max(w)}}(p(x_f) - c(x)) < c(x)$ and, at the same time, fueled by $v(P(x_f) - c(x))$. Therefore, $d(G)e^w$ is subject to whether s wants to allocate the fixed discount of x based on G or/and the w he inferred from b. In this case, s follows the rationale that, continuing assuming that $\rho_{r(\cdot)s(\cdot)} \neq 0$, $\neg\theta$ will

$$p(r_{\neg\theta}(\tilde{e}(P)))) \approx p(r_{\neg\theta}(\tilde{e}(P_{G,w})))) \approx p(r_{\neg\theta}(\tilde{e}(P_G)))) \approx p(r_{\neg\theta}(\tilde{e}(P_w))), \tag{3}$$

where $w = 0$ and $p(r_{\neg\theta}(\tilde{e}(P)))) \neq 0 \wedge \dot{\vartheta}$, where $|\dot{\vartheta} - 0| > |\dot{\vartheta} - 1|$. In contrast, where b is θ, we will observe that

$$p(r_\theta(\tilde{e}(P)))) < p(r_\theta(\tilde{e}(P_w))) \approx p(r_\theta(\tilde{e}(P_G)))) < p(r_\theta(\tilde{e}(P_{G,w})))). \tag{4}$$

Finally, s can decide not to mention the price, which we consider don't affect the probability of response if client is $\theta\tau$ and satisfies the criteria previously detailed, however, this is trickier since under this scenario we cannot infer that $\rho_{\mathrm{r}(\cdot)\mathrm{s}(\cdot)} \neq 0$.
Proposition 4. Probabilities of a response increases when discount $\mathrm{d}(G)e^{w}$increases until achieving optimal price discrimination $P_{G,w}$.
Therefore, under these propositions, we constructed the following main theorem
Theorem 1. The response rate of a bulk cold email is subject to the relationship $r(\tilde{e}) = \beta_0 + \beta_1(\check{z}, \bar{y}) + \beta_2\theta\tau\beta + \beta_3\theta\neg\tau\beta - |\beta_4|\theta\neg\tau\mu(\varphi) + \beta_5\theta\gamma(\frac{P_{G,w}}{P}) + \varepsilon$
where $(\check{z}, \bar{y})$ is a binary variable which captures whether the email satisfied or not the minimum threshold of lengthiness and presentation for each type of buyer b, β is the number of personalized items, $\mu(\varphi)$ the average time between presenting one feature from another, $\frac{P_{G,w}}{P}$ the price discrimination index, $\theta, \tau, \neg\tau$ dummy variables for whether b is part or not from the cohorts indicated, and γ a dummy that measures if price was mentioned or not.

RESULTS

We constructed a directory of 5,187 emails from CEOs of logistics companies to offer membership in a prestigious chinese logistics and freight forwarders network. The CEOs were grouped into four categories (patient, non-patient, potential, and non-potential) using proxies such as the quality of the web directory, country of origin, or the categorization previously made by the logistics network (this one categorizes companies as potential or non-potential based on their historical response rate to previous emails sent). We then sent 32 bulk cold emails, each containing an average of 167 emails, achieving an average delivery rate of 63%, a read rate of 16%, and a reply rate of 15% based on the number of emails read. Before testing the theorem, we plotted the results of our propositions (see Figure 1), which generally confirmed the expected relationships. For instance, in Proposition 1, we observed that response rates increase by 1500% when the conditions for email length and introduction timing are met for both potential and non-potential buyers. Specifically, for potential clients, failing to introduce oneself early in the email (+3 seconds) and writing an overly lengthy email (+150 words) can decrease the response probability from 32% to 2%.
In Proposition 2, we found that personalization plays a key role in response rates. Without any personalization (Personalization items = 0), the response rate was 38% for patient buyers and 16% for non-patient buyers. However, introducing just one personalization item, such as the recipient's name, reduced the response rate. Adding more detailed personalization, such as the company name (Personalization items = 2) and company location (Personalization items = 3), significantly increased response rates, suggesting that buyers may become suspicious if only their name is mentioned, since nowadays many spam emails usually uses the name of the receiver as their hook

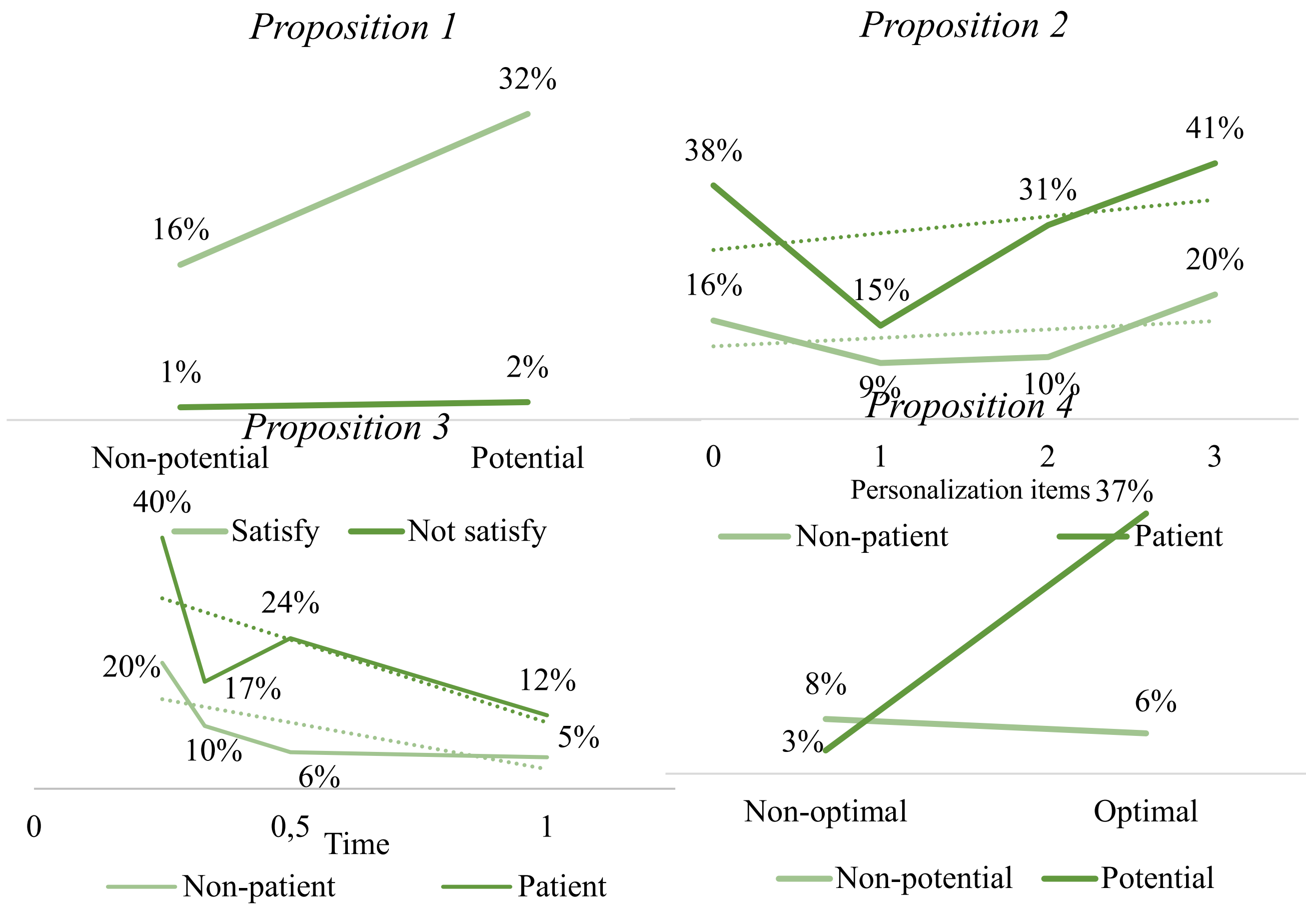
to pretend the email was tailored. Therefore, adding more items that demand more investigation about who the email receiver is somehow leads them to believe the sender is more reliable.

Fully personalized emails led to an increase in the response rate from 38% to 41% for patient buyers and from 16% to 20% for non-patient buyers. Proposition 3 revealed that reducing the time between presenting different product features in the email could significantly boost response rates. For patient buyers, the response rate increased from 12% to 40%, while for non-patient buyers, it jumped from 5% to 20%. This represents a 233% increase for patient buyers and a 300% increase for non-patient buyers, supporting our proposition that response rates grow more for non-patient buyers when feature presentation is optimized.

Finally, in Proposition 4, we tested the impact of price discrimination by introducing a dummy variable (non-optimal/optimal) representing whether the buyer received a standard price (non-optimal) or a discounted price (optimal). We found that potential buyers are more likely to respond when offered an optimal price, with an average response rate of 37%, but this drops to 3% with a non-optimal price. For non-potential buyers, however, the difference between optimal and non-optimal pricing had little effect, as they are less likely to consider the offer regardless of pricing strategy.

After finding these expected results from our propositions, we ran our econometric model from the theorem. The coefficient of $(\check{z}, \bar{y})$ (0.3352) shows a significant positive relationship with the response rate, with a p-value of 0.0119, indicating that effective email practices—such as optimal length and timely self-introduction—can substantially enhance response rates. In contrast, $\theta \neg \tau \beta$ has a coefficient of -0.0886 and a p-value of 0.0268, suggesting that certain elements, particularly for non-patient buyers, detract from the likelihood of a response. This indicates the importance of tailoring email content to the buyer's characteristics, as failure to do so may significantly lower engagement.

Figure 1. Empirics of Propositions



On the other side, $\theta\neg\tau\mu(\varphi)$ is negative and nearly significant, it suggests that non-potential buyers are sensitive to the timing of product feature presentations. When the time gap between features is larger, these buyers are less likely to respond. This aligns with the idea that non-potential buyers, who may already be less inclined to purchase, are even less interested when information is presented too slowly. Reducing the time between feature presentations might help keep them engaged, potentially increasing the chances of a response. However, since the p-value is not definitively below 0.05, the effect of $\mu(\varphi)$ on non-potential buyers should be considered cautiously.

Finally, the analysis of the beta coefficients reveals some factors such as pricing, may not be as influential, since its p-value is not statistically significant (0.1673). Therefore, the significance of coefficients (β_1, β_3, and β_4) highlights that satisfying length and presentation condition, introducing more personalization to just the patient potential cohort, and reducing the time of introducing the product features from one to another, does help to increase response rates. However, when it comes to price discrimination, the results indicate that the significance of offering optimal or non-optimal prices to consumers is relatively weak in our general model.

Table 1. *Theorem 1 Regression Results*

Variable	Coefficient	Standard Error	p-value	95% CI Lower	95% CI Upper
$\boldsymbol{Intercept}$	0.2095	0.1636	0.2005	-0.1112	0.5301
$(\boldsymbol{\check{z}}, \boldsymbol{\bar{y}})$	0.3352	0.1333	0.0119	0.0740	0.5964
$\boldsymbol{\theta\tau\beta}$	0.0646	0.0547	0.0624	-0.0033	0.1326
$\boldsymbol{\theta\neg\tau\beta}$	-0.0886	0.0400	0.0268	-0.1671	-0.0102
$\boldsymbol{\theta\neg\tau\mu(\varphi)}$	-0.2011	0.1034	0.0519	-0.4038	0.0016
$\boldsymbol{\theta\gamma(\frac{P_{G,w}}{P})}$	0.1634	0.1183	0.1673	-0.0685	0.3954

Regarding the F-test, we found statistically insignificant results (< 0.05) entailing that our main theorem as a whole lacks of validity. For which, we decide to drop the variable of price, an aspect we were aware can harm the model since some assumptions difficult to hold were used, and the personalization effect of buyers that are potential and patient. Therefore, we ran the following econometric model

$$r(\tilde{e}) = \beta_0 + \beta_1(\check{z}, \bar{y}) + \beta_2\theta\neg\tau\beta - |\beta_3|\theta\neg\tau\mu(\varphi) + \varepsilon, \qquad (5)$$

having the following results

Table 2. *Reviewed Regression Results*

Variable	Coefficient	Standard Error	p-value	95% CI Lower	95% CI Upper
$\boldsymbol{Intercept}$	0.17208	0.166406	0.309934	-0.51295	0.168785
$(\boldsymbol{\check{z}}, \boldsymbol{\bar{y}})$	0.273445	0.077371	0.001442	0.114958	0.431933
$\boldsymbol{\theta\neg\tau\beta}$	0.144776	0.059658	0.021923	0.022572	0.266981
$\boldsymbol{\theta\neg\tau\mu(\varphi)}$	-0.171244	0.074956	0.036068	-0.18714	0.529625

Our ANOVA results show statistical significance, which makes our new regression model robust enough to explain the factors that should be considered to increase response rates. As we found, email length, sender presentation timing, personalization, and product's features presentation timing are the variables that strongly influence changes in response rates. This provides clearer insights into how a bulk cold email should be structured to achieve higher response rates and, therefore, more sales.

CONCLUSIONS

We proposed a mathematical model that systematically captures the decision-making process involved in sending bulk cold emails. Our empirical findings revealed that some traditionally cited variables, such as price discrimination, are not statistically significant in increasing response rates in our model. Indeed, our analysis indicates that only three key factors significantly contribute to improving email response rates: the email length combined with the timing of the sender's presentation, the degree of personalization for non-patient buyers, and the presentation of product features to potential non-patient buyers.

Our findings show that if an email is lengthy, lacks personalization, has excessive delays between the presentation of product features, and the sender fails to introduce themselves formally, the response rate decreases to 17%. However, optimizing the structure can lead to significantly better response rates. For instance, if the sender writes a concise cold email, no longer than 150 words, and introduces themselves immediately after the start of the email (between the 3 seconds threshold), the expected response rate jumps to 44%. In addition, when targeting non-patient potential buyers, increasing the level of personalization increases the response rate to 58%. Interestingly, our experiment found that simply mentioning the potential customer's name could reduce trust, as it may rise some sort of distrust due to how common has become the practice of just using the name by spammers. To build trust, it is crucial to include the company's name and location, reassuring the recipient that the email is legitimate and not a scam. Additionally, minimizing the time between the presentation of each product feature is essential, as any unnecessary delay decreases the probability of a response.

Finally, we acknowledge certain limitations in our experiment, particularly the use of proxy variables to classify buyers, which may introduce bias into our results. Furthermore, there is a need for deeper investigation into the relationship between price discrimination and response rates, as potential miscalculations regarding affordability for different cohorts may have affected the accuracy of our results. In addition, we hypothesize that the model may omit variables such as country of origin and sex of the sender, country of the company, or any other psychological biases which are hard to aggregately investigate both mathematical and empirically. The emails of our experiment were sent under a salesman from Latin American working in China, which it is needed to explore deeply whether how subjective characteristics shape the decision-making process of the receiver, affecting indirectly their willingness to reply. By addressing these issues in future research, we aim to further refine the model and enhance our understanding of the dynamics behind cold email response rates.

REFERENCES

Aufreiter, N., Boudet, J., & Weng, V. (2014, January 1). Why marketers should keep sending you e-mails. Mckinsey & Company. https://www.mckinsey.com/capabilities/growth-marketing-and-sales/our-insights/why-marketers-should-keep-sending-you-emails/

Collis, K. (2020, April). The science behind cold emails that work. Liinea. https://liinea.com/coldemailpart1

Dean, B. (2019, April 16). We analyzed 12 million outreach emails here's what we learned. Backlinko. https://backlinko.com/email-outreach-study

Gartner. (2019, August 30). Sales development technology: the stack emerges. Gartner. https://www.gartner.com/en/articles/sales-development-technology-the-stack-emerges

Keohane, J. (2021, May 26). 20 cold email subject lines proven to get over 85% open rates. Yesware. https://www.yesware.com/blog/cold-email-subject-lines/

Le Plaisir, B. (2024, February). Specific target: how important is personalization in cold emails. American Institute for Research & Innovation. 10.13140/RG.2.2.27901.13283

Rodrigues, A. (2024, September 19). Cold email guide for small businesses: strategies to get noticed. Pipedrive. https://www.pipedrive.com/en/blog/cold-email-guide

Siewierska, M. (2024, February 5). Cold email statistics based on sending over 20M cold emails. Woodpecker. https://woodpecker.co/blog/cold-email-statistics/

Suresh, S. (2023, July 14). 30+ Cold email statistics you need to know in 2023. Outplay. https://outplayhq.com/blog/cold-email-statistics

Tucker, M. (2016, September 20). A guide to cold emailing. Harvard Business Review. https://hbr.org/2016/09/a-guide-to-cold-emailing