Predicting the Diffusion Pattern of Internet-Based Communication Applications Using Bass Model Parameter Estimates for Email

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Abstract
The continuing evolution of the Internet as a major tool of communication has provided new sender/receiver applications such as email, blogs, forums and Voice over Internet Protocol. Many of these Internet-based communication applications have proven to be very popular amongst consumer groups. But when can we expect the diffusion of these new innovations to reach critical mass? The authors seek to determine when peak adoption will be reached for such Internet-based communication applications by examining the diffusion pattern of a mature application – that of email. The authors propose that Bass model parameter estimates for email can serve as an approximation of parameter estimates for other products within the domain of similar Internet-based communication applications. This study drew upon 10 years of diffusion data, and the Bass Model approach was utilised to classify individuals into adopter categories. The results revealed a q/p ratio of 50.7 for the adoption of email; indicating that the imitation effect is greater than the innovation effect in the diffusion of similar Internet-based communication technologies. It was also found that for such technologies, the peak of the non-cumulative adoption curve can be expected in 5.4 years after launch. In the case of Twitter, for example, which was launched in September 2006, critical mass is predicted to occur in early-2012.

Keywords: Innovation, Diffusion, Adoption, Communication Technology, Bass Model.
**Introduction**

The exchange of ideas via new electronic platforms is of vital interest to marketers. The Internet, a computer network originally conceived as a tool for communication, has provided a number of communication applications that are helping to shape the way consumers interact with each other and with businesses. Internet-based communication applications such as Twitter, broadcast mini massages via hardware connected to the Internet (for example, a personal computer or mobile phone). In the case of Twitter, an individual message is referred to as a ‘Tweet’ and can be sent to one or many fellow ‘Twitterers’. The blogged messages tend to be light-weight updates detailing ones’ status - daily activities and opinions (Java et al. 2007), and interested observers ‘follow’ an individual or business’s blog and if they choose, can comment on their ‘tweets’.

Whether via blogs, pictures or videos, consumers are sharing their personal opinions, hopes and dreams with the rest of the world like never before. With access readily available to the masses and topics of interest limited only by human imagination, the growth rate of these applications has been exceptional. My Space attracted 150 million members in its first three years (Schultz 2007) and Twitter has published over 20 billion messages since its launch in 2006 (Williams 2010).

Like all innovations however, the explosive growth of such technologies will eventually begin to diminish. The time will come when the majority of those who intend to adopt a technology would have already done so. Diffusion theory (Rogers 1983) logically holds that after the peak of the adoption curve has been reached, adoption thereafter starts to decline. Knowledge of this point in time may help managers at companies such as Twitter to make more accurate estimates of advertising revenue and more effective marketing strategies relating to each stage of its product life cycle.

The Bass Model (1969) has been used by numerous researchers to forecast demand of future products based on the diffusion data collected from a previous similar innovation (Bass 1969; Mahajan et al. 1990; Martinez et al. 1998). But as Lilien and Rangaswamy (2003) point out, the Bass Model has most commonly been used to study the adoption of physical goods. This research extends the use of the Bass Model to calculate parameter estimates for an Internet-based communication application that has surpassed the peak of its adoption curve, namely email.
Logical arguments are presented that support the diffusion pattern of email being used to serve as a bellwether for more contemporary communication technologies which serve the same purpose.

**Theoretical framework**

Innovativeness is a personality trait underlying the adoption of innovations. Leavitt and Walton (1975, 1988) describe innovators as individuals open to new experiences and who have a heightened sensitivity in recognizing the potential value of new concepts, ideas, products and services.

Individuals who may be seen as innovators in one product domain, however, may not necessarily be innovators in other domains. Indeed, research conducted by Gatignon and Robertson (1985), Citrin et al. (2000), Goldsmith (2001) and Blake et al. (2003) contends that innovativeness must be identified and characterized on a specific product category or domain basis. Heavy users of a product within the domain have greater experience with the product and are thought to be more likely to innovate and adopt a new related product. Measurement scales developed by Goldsmith and Hofacker (1991), therefore, are domain-specific and reflect an individual’s tendency to learn about and adopt innovations within a particular area of interest.

Another approach to measuring innovativeness is to determine the individual’s adopter category on the basis of the relative time of adoption of the innovation. Rogers (2003 p. 22), defines a person’s innovativeness as ‘the degree to which an individual is relatively earlier in adopting new ideas than other members of a social system’. The measurement would then be used to classify individuals into adopter categories such as innovators, early adopters, early majority, late majority and laggards. The time lag of adoption can then be used to predict the diffusion of future similar innovations.

The categorization scheme proposed by Rogers (1983, 1995), however, has potential limitations. Several researchers have argued that Roger’s assumptions that all new products follow a normal-distribution diffusion pattern, and that the size of the adopter categories are the same for all new products is questionable (Peterson 1973). Also, unlike Rogers, some researchers have sought to distinguish between true innovators and imitative early adopters (Mahajan et al. 1985). Rogers’ (2003) definition of innovativeness is solely time-dependent and requires a product launch if it is to be observed and measured. According to this understanding
those who adopt early are assumed to be innovators. However, McDonald and Alpert (2007) argue that innovators are much more than just early adopters. Using the psychological trait definition of innovativeness laid down by Midgley (1977), and Midgely and Downing (1978); McDonald and Alpert (2007) take the emphasis away from time and instead focus on the information type used by the consumer when deciding whether to adopt. Decisions leading to adoption that are made independent of word-of-mouth are thought to be made by true innovators, while those dependent upon word-of-mouth are referred to as imitators. Hence, an innovative individual reliant on mass media advertising rather than interpersonal communications could make the decision to adopt at any stage of Roger’s (2003) diffusion pattern. What matters is how the individual has been marketed to, not the amount of time elapsed since the product was launched. This definition is thought to give a greater understanding of diffusion as it isolates the source of information used in the decision making process.

Using the same analytical logic underlying the adopter categorization approach proposed by Rogers (1983), Mahajan et al. (1990) suggest that adopter categories can also be developed using other well-established diffusion models, such as the Bass Model (Bass 1969). The exponential growth commonly observed during product diffusion (the S-curve) is, according to Bass (1969), largely a result of communicated experience (i.e. adopters telling others about the new product). In this way, the Bass Model overcomes Roger’s limitations by categorising consumers as ‘innovators’ or ‘imitators’ on the basis of their reliance on word-of-mouth.

The Bass (1969) model, however, is not without its imperfections. Parameter estimates of the Bass model may be not be stable for relatively new products because adoption data are limited. Studies suggest that stable and robust parameter estimates for the Bass model are obtained only if the data under consideration include the peak of the non-cumulative adoption curve (Heeler and Hustad 1980; Srinivasan and Mason 1986; Bemmaor and Lee 2002; Boswijk and Franses 2005). This poses a problem when modelling the diffusion of recently launched Internet-based communication applications such as Twitter, as many of these current applications are still in their early stages of their adoption. Therefore attempts to measure the diffusion pattern of these relatively new products directly may harvest incomplete data and less-than-reliable results.
The contribution of this paper is thus to provide a basis for measuring the diffusion pattern of Internet-based communication applications by synthesizing two major diffusion concepts - firstly, the methods derived from Roger’s adoption categories (1983) and the Bass Model (1969); and secondly, the premise of characterizing innovativeness on a product category or domain basis (Gatignon and Robertson 1985; Citrin et al. 2000; Goldsmith 2001; Blake et al. 2003). The approach this paper has taken was therefore to collect adoption data for a mature product within the domain of Internet-based communication applications, which has surpassed the peak of its diffusion curve. We propose that an examination of email adoption may provide some insight into the diffusion pattern of other more recent Internet-based communication technologies such as Twitter. We perceived email to be an appropriate bellwether technology for Twitter because both technologies share the same product domain. We provide merit for this claim with the following points: (1) email is a predecessor technology that has already reached maturity in most markets; (2) participation in Twitter (microblogging) requires an established email address; (3) email and Twitter are both used *primarily* to exchange daily chatter, as well as, share information and news (Java et al. 2007); (4) communication flow in both mediums can be one-to-one, one-to-many, or many-to-one; (5) both technologies are asynchronous online communication mediums which are well-suited to large and diverse personal networks (Gibson 2005); and (6) family, friends, and co-workers can be influenced to sign-up to the email or Twitter networks either through mass media advertising appeals, invitations by existing members, or word-of-mouth persuasion.

Based on the preceding arguments, an estimation of the Bass model parameters for email adoption may thus serve as an approximation of the diffusion pattern for Twitter and other Internet-based communication applications that share similar characteristics and purpose, but whose diffusion pattern cannot yet be reliably measured because the peaks of their non-cumulative adoption curves have not yet occurred. Until other asynchronous Internet-based communication technologies reach their peaks, there are no better data available to make such predictions.
Determination of adopter categories using the Bass model

The Bass Model suggests that the probability of purchase (or in this case online membership registration) at a given point in time is a linear function of the total proportion of previous buyers driven by external influences (mass media) and internal influences (word-of-mouth) (Mahajan et al. 1990; Goldenberg et al. 2001).

\[ P(t) = p + qF(t) \] \[1\]

Where:
- \( P(t) \) = probability of purchase
- \( F(t) \) = total proportion of previous buyers
- \( p \) = coefficient of innovation (external influence)
- \( q \) = coefficient of imitation (internal influence)

The number of adopters at a given time is the number of people who have not adopted yet times their probability of purchase.

\[ f(t) = [1 - F(t)]P(t) \] \[2\]

Substituting [1] into [2] yields the following equation:

\[ f(t) = p + [q - p]F(t) - qF(t)^2 \] \[3\]

The total proportion of previous buyers is modelled by Bass as follows:

\[ F(t) = \frac{1-e^{-(p+q)t}}{1+(q/p)e^{-(p+q)t}} \] \[4\]

Therefore by substituting [4] into [3], yields the following model:
Differentiating [5] with respect to time gives:

\[ f'(t) = \frac{-p(p+q)^3 e^{-(p+q)t}}{(p + qe^{-(p+q)t})^3} \left[ p - qe^{-(p+q)t} \right] \]  

[6]

And taking the second derivative of [5] with respect to time gives:

\[ f''(t) = \frac{-p(p+q)^4 e^{-(p+q)t}}{(p + qe^{-(p+q)t})^4} \left[ (p + qe^{-(p+q)t})(-p + 2q e^{-(p+q)t}) + 3q e^{-(p+q)t} (p - qe^{-(p+q)t}) \right] \]  

[7]

Solving [6] for \( t \) when \( f'(t) = 0 \) gives:

\[ T^* = -\frac{1}{(p + q)} \ln \left[ \frac{p}{q} \right] \]  

[8]

Solving [7] for \( t \) when \( f''(t) = 0 \) gives two solutions:

\[ T_i = -\frac{1}{(p + q)} \ln \left[ \frac{2 + \sqrt{3}}{2} \frac{p}{q} \right] \]  

[9]

and:

\[ T_2 = -\frac{1}{(p + q)} \ln \left[ \frac{1}{2 + \sqrt{3}} \frac{p}{q} \right] \]  

[10]
Figure 1 provides a graphical representation of the above functions.

\[ F(t) : \text{Cumulative proportion of adopters} \]
\[ F(t) = \frac{1 - e^{-(p+q)t}}{1 + (q/p)e^{-(p+q)t}} \]

\[ f(t) : \text{Noncumulative proportion of adopters} \]
\[ f(t) = \frac{p(p+q)e^{-(p+q)t}}{(p+q/3)e^{-(p+q)t} + (p+q/2)e^{-(p+q)t} + (p+q)e^{-(p+q)t}} \]

First derivative of \( f(t) \) w.r.t. time
\[ f'(t) = \frac{-p(p+q)e^{-(p+q)t}}{(p+q/3)e^{-(p+q)t} + (p+q/2)e^{-(p+q)t} + (p+q)e^{-(p+q)t}} \left[ p - qe^{-(p+q)t} \right] \]

Second derivative of \( f(t) \) w.r.t. time
\[ f''(t) = \frac{-p(p+q)e^{-(p+q)t}}{(p+q/3)e^{-(p+q)t} + (p+q/2)e^{-(p+q)t} + (p+q)e^{-(p+q)t}} \left[ (p+q)e^{-(p+q)t} \right] \]
\[ -p + 2qe^{-(p+q)t} + 3qe^{-(p+q)t} \left[ (p+q)e^{-(p+q)t} \right] \]

\[ T_1 = -\frac{1}{(p+q)} \ln \left( \frac{(2 + \sqrt{3})p}{q} \right) \]
\[ T_2 = -\frac{1}{(p+q)} \ln \left( \frac{1}{(2 + \sqrt{3})q} \right) \]
\[ T' = -\frac{1}{(p+q)} \ln \left( \frac{p}{q} \right) \]

Figure 1: Determination of adopter categories using the Bass model
Data collection method
Following the description of the Bass model in the earlier section, the only data required to successfully model the diffusion pattern of an innovation is the time of its adoption. A commercially-purchased nationwide database of 2,500 names and addresses was used as a sampling frame for a mail survey. The use of a four-stage pre-notification procedure yielded an overall response rate of 30.6%.

Respondents to the survey were asked to indicate the year they first started using email. Of the 611 respondents to the questionnaire, 589 responded to the question. 41 respondents indicated that they had not yet started using email, while 44 respondents indicated that they had started using email prior to 1993. These 44 responses were discarded from use in the calculation of the diffusion pattern due to the fact that commercial email services were not yet online prior to 1993 (Hardy 1996), making it unclear whether email was actually adopted during that time or an alternative electronic messaging service.

Analysis and discussion
The resulting data yielded 10 years of diffusion data that is summarised in Table 1, where the percentages (%) column indicate the noncumulative diffusion pattern of email and the cumulative percentages (Cum. %) column indicate the cumulative diffusion pattern of email.

<table>
<thead>
<tr>
<th>Year</th>
<th>Freq</th>
<th>%</th>
<th>Cum %</th>
<th>Year</th>
<th>Freq</th>
<th>%</th>
<th>Cum %</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>8</td>
<td>1.47</td>
<td>1.47</td>
<td>6</td>
<td>107</td>
<td>19.63</td>
<td>60.92</td>
</tr>
<tr>
<td>2</td>
<td>23</td>
<td>4.22</td>
<td>5.69</td>
<td>7</td>
<td>74</td>
<td>13.58</td>
<td>74.50</td>
</tr>
<tr>
<td>3</td>
<td>69</td>
<td>12.66</td>
<td>18.35</td>
<td>8</td>
<td>72</td>
<td>13.21</td>
<td>87.71</td>
</tr>
<tr>
<td>4</td>
<td>57</td>
<td>10.46</td>
<td>28.81</td>
<td>9</td>
<td>20</td>
<td>3.67</td>
<td>91.38</td>
</tr>
<tr>
<td>5</td>
<td>68</td>
<td>12.48</td>
<td>41.28</td>
<td>10</td>
<td>6</td>
<td>1.10</td>
<td>92.48</td>
</tr>
</tbody>
</table>

Table 1: Year respondent first began using email

Figure 2 gives a graphical representation of the noncumulative diffusion pattern \( f(t) \). An estimation of the smooth Bass curve is shown superimposed over the top. As previously described, the timing \( T^* \) indicate the point where the diffusion pattern of email has reached critical mass or where \( f(t) \) has peaked. Similarly, the cumulative diffusion pattern \( F(t) \) is shown...
in Figure 3. Here, an estimation of the Bass cumulative diffusion S-shape curve is also shown superimposed. The same timing $T^*$ where diffusion has reached critical mass found in Figure 2 must also be the point of inflection of the cumulative diffusion curve in Figure 3, as is indicated.

In this paper, we describe the process used in providing a solution for the Bass model parameters through a process of initial graphical estimation and re-verification of $T^*$ in an iterative manner. The use of a statistical software package to fit the Bass curve to the data was not pursued due to the limited number of data-points available (i.e. 10 data-points for 10 years of data). The iterative process of estimation and verification used in this research therefore provided the necessary crosschecks to ensure accuracy of $T^*$ is maintained. Subsequent parameters of the Bass model $q$, $p$, $T_1$ and $T_2$ will then be calculated using the equations [8], [9] and [10] described earlier.

Firstly, from Figures 2 and 3, we graphically estimate the point $T^* = 5.4$, which coincide with both the peak of the noncumulative diffusion pattern $f(t)$ as well as the point of inflection on the cumulative diffusion pattern $F(t)$. The noncumulative and cumulative percent penetration at these points are thus estimated to be $f(T^* = 5.4) = 0.185$ and $F(T^* = 5.4) = 0.490$ respectively.

![f(t): Noncumulative Diffusion Pattern](image)

**Figure 2:** Noncumulative diffusion pattern showing graphical estimation of $T^*$
Bass model parameter estimation

From these estimates, we now calculate the parameters $p$ and $q$ of the Bass model using the equations described in the previous section.

Firstly, we substitute [8] into [4] for $t=T^*$ to derive $F(T^*)$ as follows.

$$F(T^*) = \frac{1}{2} - \frac{p}{2q}$$  \hspace{1cm} [11]


$$f(T^*) = \frac{1}{4q} (p + q)^2$$  \hspace{1cm} [12]

We now simply substitute our graphical estimates of $f(T^*=5.4) = 0.185$ and $F(T^*=5.4) = 0.490$ into [11] and [12] yielding 2 equations bearing the parameters $p$ and $q$. Solving these equations simultaneously will thus give us the values for $p$ and $q$. The workings are as follows.
Substituting $F(T^*=5.4) = 0.490$ into [11] gives:

$$0.490 = \frac{1}{2} \frac{p}{2q} \tag{A}$$

Simplification yields:

$$p = 0.02q \tag{B}$$

Substituting $f(T^*=5.4) = 0.185$ into [12] gives:

$$0.185 = \frac{1}{4q} (p + q)^2 \tag{C}$$

Substituting [B] into [C] gives:

$$0.185 = \frac{1}{4q} (0.02q + q)^2 \tag{D}$$

Solving for $q$ gives:

$$q = 0.711 \tag{E}$$

Substituting [E] back into [B] gives:

$$p = 0.014 \tag{F}$$

For the purpose of verifying the accuracy of our initial graphical estimate of $T^*=5.4$, we substitute our calculated values of $p$ and $q$ back into [8] yielding:
\[ T^* = -\frac{1}{(0.014 + 0.711)} \ln \left( \frac{0.014}{0.711} \right) \]  

\[ T^* = 5.392 \]  

\[ T^* = 5.4 \text{ (rounded to one decimal place)} \]

The above calculated value of \( T^* = 5.4 \) reconfirms the accuracy of our initial graphical estimates. Should the value of \( T^* \) not be confirmed, the estimate may be refined, re-calculated and re-verified iteratively.

We have now solved the parameters \( q \) and \( p \) of the Bass model (\( 0.711/0.014 = 50.7 \)). The original Bass (1969) parameters for household electrical products ranged from 9.0 to 85.7; Mahajan et al. (1990) on the diffusion of microcomputers yielded a \( q/p \) ratio of 29.0 and Martinez et al. (1998) found various white goods to have a ratio between 6.5 and 117. Higher values of the ratio \( q/p \) indicate that adoption of the product exhibits a relatively higher imitation effect than innovation effect, and the lower the values indicate that the adoption of the product exhibits a relatively higher innovation effect than imitation effect.

Compared to the range indicated by past research (Bass 1969; Mahajan et al. 1990; Martinez et al. 1998), the diffusion pattern for the adoption of email shows a relatively high \( q/p \) ratio (50.7). This finding suggests that the adoption of email is mostly due to the imitation effect (for example, through word of mouth), where people choose to adopt because other people have already adopted. Personal innovativeness or response to mass advertising (innovation effect) is less likely to lead to adoption. This is consistent with the dyadic nature of email: both the sender and the receiver of an email had to have adopted the technology before effective communication can take place. The value of email as a communication technology is predicated upon the number of associates who adopt it. This notion implies that other Internet-based communication technologies may exhibit similarly high \( q/p \) ratios.

Satisfied with the verified values of \( T^* \), \( p \) and \( q \), we now solve for \( T_1 \) and \( T_2 \) as follows.
Substituting the values from [E] and [F] into [9] gives:

\[ T_1 = -\frac{1}{(0.014 + 0.711)} \ln \left( \frac{2 + \sqrt{3} \cdot 0.014}{0.711} \right) \]  

\[ T_1 = 3.577 \]  

And substituting the values from [E] and [F] into [10] gives:

\[ T_2 = -\frac{1}{(0.014 + 0.711)} \ln \left( \frac{1}{2 + \sqrt{3} \cdot 0.014} \right) \]  

\[ T_2 = 7.208 \]

Table 2 provides a summary of the values calculated in the preceding section.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Calculated Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>p</td>
<td>0.014</td>
</tr>
<tr>
<td>q</td>
<td>0.711</td>
</tr>
<tr>
<td>q/p ratio</td>
<td>50.7</td>
</tr>
<tr>
<td>T1</td>
<td>3.577</td>
</tr>
<tr>
<td>T*</td>
<td>5.392</td>
</tr>
<tr>
<td>T2</td>
<td>7.208</td>
</tr>
</tbody>
</table>

Table 2: Summary of calculated values for the Bass model

**Determination of adopter categories for email and innovativeness**

Using the parameter estimates derived in the previous section, it is now possible to examine the innovativeness of the individual with respect to their time of adoption of email.

Figure 4 proposes the adopter categorisation developed from the Bass diffusion model. It clearly shows the values of T1, T*, and T2 used to divide the Bass diffusion curve into 4 sections of adopter categories, with innovators indicated by the number of adopters at t = 1.
To find the proportion of adopters in each of the adopter categories based on the Bass model parameters, it is simply a matter of calculating the cumulative number of adopters $F(t)$ using the equation described in [4] at each of $T_1$, $T^*$ and $T_2$ respectively, and subtracting the proportion in the previous categories. Table 3 gives a summary of the workings.

<table>
<thead>
<tr>
<th>Adopter Category</th>
<th>Time Duration (Years)</th>
<th>% Adopters (Bass Model)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Innovators</td>
<td>-</td>
<td>$p$</td>
</tr>
<tr>
<td>Early Adopters</td>
<td>$T_1$</td>
<td>$F(T_1)-p$</td>
</tr>
<tr>
<td>Early Majority</td>
<td>$T^*-T_1$</td>
<td>$F(T^*)-F(T_1)$</td>
</tr>
<tr>
<td>Late Majority</td>
<td>$T_2-T^*$</td>
<td>$F(T_2)-F(T^*)$</td>
</tr>
<tr>
<td>Laggards</td>
<td>Beyond $T_2$</td>
<td>$1-F(T_2)$</td>
</tr>
</tbody>
</table>

Table 3: Calculation of time duration and percentage of adopters using the Bass model
The results from the Bass model were not expected to fit perfectly with the observed data gathered in this study – naturally there was some degree of error in the modelled data. It is therefore important to determine the extent to which the size of each adopter category (observed data) differs from that modelled. Table 4 shows how the size of the adopter categories is derived from the observed data using the same cut-off points as determined by $T_1$, $T^*$ and $T_2$. Table 5 provides a summary of the findings and compares the size of adopter categories between observed and that modelled using the Bass approach. From Table 5, we are able to see a close fit between the modelled and observed data except for the category of early majority where the actual data lags behind the model, but catching up with the late majority and laggards.

<table>
<thead>
<tr>
<th>Adopter Category</th>
<th>Year</th>
<th>Freq</th>
<th>%</th>
<th>Cum %</th>
<th>% Cat</th>
</tr>
</thead>
<tbody>
<tr>
<td>Innovators</td>
<td>1</td>
<td>8</td>
<td>1.47</td>
<td>1.47</td>
<td>1.47</td>
</tr>
<tr>
<td></td>
<td>2</td>
<td>23</td>
<td>4.22</td>
<td>5.69</td>
<td>16.88</td>
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<tr>
<td></td>
<td>3</td>
<td>69</td>
<td>12.66</td>
<td>18.35</td>
<td></td>
</tr>
<tr>
<td>Early Adopters</td>
<td>4</td>
<td>57</td>
<td>10.46</td>
<td>28.81</td>
<td>22.94</td>
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<td>68</td>
<td>12.48</td>
<td>41.28</td>
<td></td>
</tr>
<tr>
<td>Early Majority</td>
<td>6</td>
<td>107</td>
<td>19.63</td>
<td>60.92</td>
<td>33.21</td>
</tr>
<tr>
<td></td>
<td>7</td>
<td>74</td>
<td>13.58</td>
<td>74.50</td>
<td></td>
</tr>
<tr>
<td>Late Majority</td>
<td>8</td>
<td>72</td>
<td>13.21</td>
<td>87.71</td>
<td>25.50</td>
</tr>
<tr>
<td></td>
<td>9</td>
<td>20</td>
<td>3.67</td>
<td>91.38</td>
<td></td>
</tr>
<tr>
<td></td>
<td>10</td>
<td>6</td>
<td>1.10</td>
<td>92.48</td>
<td></td>
</tr>
<tr>
<td>Laggards</td>
<td></td>
<td>41</td>
<td>7.52</td>
<td>100.00</td>
<td></td>
</tr>
<tr>
<td>Not yet adopted</td>
<td>-</td>
<td>41</td>
<td>7.52</td>
<td>100.00</td>
<td></td>
</tr>
</tbody>
</table>

Table 4: Year first began using email and adopter category classification

<table>
<thead>
<tr>
<th>Adopter Category</th>
<th>Time Duration (Years)</th>
<th>% Adopters (Bass Model)</th>
<th>% Adopters (Observed)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Innovators</td>
<td>-</td>
<td>1.4</td>
<td>1.47</td>
</tr>
<tr>
<td>Early Adopters</td>
<td>3.6</td>
<td>18.2</td>
<td>16.88</td>
</tr>
<tr>
<td>Early Majority</td>
<td>+1.8</td>
<td>29.4</td>
<td>22.94</td>
</tr>
<tr>
<td>Late Majority</td>
<td>+1.8</td>
<td>29.4</td>
<td>33.21</td>
</tr>
<tr>
<td>Laggards</td>
<td>Beyond 7.2</td>
<td>21.5</td>
<td>25.50</td>
</tr>
</tbody>
</table>

Table 5: Comparison of adopter category size between modelled and observed data
How does this data compare with previous research on the size of adopter categories? Table 6 shows the adopter distribution using a normal distribution curve as originally proposed by Rogers (1995), results from extensive past research on a variety of products by Bass (1969), and how the data derived from this research compares. Here, we see that the modelled data provides acceptable adopter category sizes that are all within the ranges proposed in past research, pointing again to the accuracy of the Bass parameter estimates we derived earlier and the usefulness of using the Bass model in determining adopter categories for the adoption of email.

<table>
<thead>
<tr>
<th>Adopter Category</th>
<th>Past Research</th>
<th>This Research</th>
<th>Comment on Modelled Data</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Normal Adopter Distribution (%) (Rogers)</td>
<td>Bass Adopter Distribution (%) (Bass)</td>
<td>Adopter Distribution (%)</td>
</tr>
<tr>
<td>Innovators</td>
<td>2.5</td>
<td>0.2 to 2.8</td>
<td>1.4</td>
</tr>
<tr>
<td>Early Adopters</td>
<td>13.5</td>
<td>12.3 to 20.2</td>
<td>18.2</td>
</tr>
<tr>
<td>Early Majority</td>
<td>34</td>
<td>29.1 to 32.1</td>
<td>29.4</td>
</tr>
<tr>
<td>Late Majority</td>
<td>34</td>
<td>29.1 to 32.1</td>
<td>29.4</td>
</tr>
<tr>
<td>Laggards</td>
<td>16</td>
<td>21.4 to 23.5</td>
<td>21.5</td>
</tr>
</tbody>
</table>

Table 6: Comparing size of adopter categories in past research (from Mahajan et al. 1990)

Demographic differences between adopter categories for email

Given the small number of innovators (8 respondents – 1.47%), innovators are combined with early adopters to examine the differences between adopter categories. After combining innovators with early adopters, the resulting category sizes are as shown in Figure 5.
The number of respondents in each adopter category is now compared with respect to their gender, age, highest formal qualification, and main education background. Table 7 shows the Chi-Square statistic ($\chi^2$) for each of these demographic variables. It is found that age and highest formal qualification had significant relationships with adopter categories.

<table>
<thead>
<tr>
<th>Demographic Variable</th>
<th>Chi-Sq.</th>
<th>($\chi^2$)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>4.417</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>30.935</td>
<td>***</td>
</tr>
<tr>
<td>Highest Formal Qualification</td>
<td>56.060</td>
<td>***</td>
</tr>
<tr>
<td>Main Education Background</td>
<td>35.684</td>
<td></td>
</tr>
</tbody>
</table>

*** Significant at $p = 0.01$

Table 7: Demographic differences between adopter categories for email

Tables 8 and 9 closely examine the exact differences between the different age and highest formal qualification groupings. The groupings for highest formal qualifications are divided into various educational levels – primary school, completed secondary school, trade qualification/diploma, tertiary degree, and postgraduate qualifications.
### Table 8: Age differences between adopter categories for email

<table>
<thead>
<tr>
<th>Personal: Age</th>
<th>Count</th>
<th>Expected Count</th>
</tr>
</thead>
<tbody>
<tr>
<td>20 - 29</td>
<td>7</td>
<td>5.0</td>
</tr>
<tr>
<td>30 - 39</td>
<td>12</td>
<td>13.6</td>
</tr>
<tr>
<td>40 - 49</td>
<td>32</td>
<td>24.2</td>
</tr>
<tr>
<td>50 - 59</td>
<td>36</td>
<td>39.1</td>
</tr>
<tr>
<td>60+</td>
<td>13</td>
<td>18.2</td>
</tr>
<tr>
<td>Total</td>
<td>100</td>
<td>100.0</td>
</tr>
</tbody>
</table>

(+): Indicates Observed Count Higher than Expected

It is observed that the lower age groups (20 years to 49 years) are more likely to be early adopters or early majority than the higher age groups – these having observed counts greater than expected counts as shown in Table 8. The higher age groups (50 and above) are more likely to be in the late majority or laggards categories. This finding is consistent with diffusion literature.
that indicates more innovative people tend to be younger (Wang et al. 2008; Martinez et al. 1998; Rogers 1995).

Table 9 shows a clear relationship between highest formal qualification and adopter categories. It is observed that lower educational categories tend to be in the late majority or laggard category, while higher educational categories tend to be either in the early adopter or early majority adopter categories – as shown by their higher observed count than expected counts. This finding is also consistent with past research by Rogers (1983, 1995).

Conclusions and implications
The results of this study have provided an approach to model the diffusion of email. We have extended the use of the Bass Model to include Internet applications, not just physical products. Despite the age of the Bass Model, we have found it to be highly relevant and a useful forecasting method. Its limited application in the online context is surprising. We hope this study fills this gap and validates a new direction in the extension of the Bass Model for the forecasting of Internet-based communication technologies.

As discussed, one’s level of innovativeness may be applied to other forms of technology adoption to the limits of the domain occupied by email technology— that of Internet-based communication applications. In relation to this domain (which includes applications such as Twitter), our research suggests answers to three important questions: (1) what will influence the decision to adopt (internal or external influence); (2) what are the demographic characteristics of adopters; and (3) what is the estimated timing of peak adoption?

Our calculated q/p ratio of 50.7 was within range when compared to past research (Bass 1969; Mahajan et al. 1990; Martinez et al. 1998). This suggests that the decision to adopt an innovation within this domain is mostly imitative, influenced by word-of-mouth. Only a very small percentage (1.47%) was found to be true innovators. The results also show that highly educated younger individuals exhibit a greater tendency to adopt Internet-based communication applications. These findings are also consistent with past research (Rogers 1983, 1995; Wang et al. 2008; Martinez et al. 1998).

Working with the premise that products with similar characteristics and purpose are likely to possess similar q/p ratios, this research makes a strong case for forecasting the timing of
adopter categories, and overall timing of peak adoption for Internet-based communication applications. Our research forecasts peak adoption to be reached 5.4 years after launch. In the case of Twitter, which was launched in September 2006, the peak of the adoption curve in lead markets such as the United States can be expected in early-2012. This has implications for organizations that run such websites, for they will benefit from knowing the speed of adoption and when to expect diminishing membership growth and eventual decline. This knowledge can assist managers in establishing more timely budgets with regards to advertising rates and potential advertising revenue. Managers can also use this knowledge to establish the timing and duration of each stage of the product life cycle, and in turn, implement the appropriate marketing strategies for the corresponding stages.

Like-minded innovative consumers are finding each other using Internet-based communication applications and marketers should not be too far behind. Additional research is needed to determine the scope of forecasting within a domain. Just how similar do two products within the same domain have to be in the minds of consumers for any meaningful forecasting to take place? What essential characteristics must these technologies share? The establishment of equivalence is vital as it will help determine the extent to which earlier technologies can be used to approximate the diffusion patterns of other technologies. Researchers would benefit from future studies on the extent to which email can be generalizable to other Internet technologies beyond basic Twitter-type communication to other social networking and file-sharing applications such as My Space and Facebook.

References


