VIRTUAL NETWORKING AND THE TRANSFORMATIONOF INTERPERSONAL RELATIONSHIPS

Elveena Joy, Om Sirohi, Rajgyal Gurung, Riya Jain , Dr . K.Geetha
Student , Student , Student ,Student , Assistant Professor & PCL Guide
Department of Languages,(English)
SCHOOL OF HUMANITIES AND SOCIAL SCIENCES
Jain Deemed To Be University, Bengaluru, Karnataka

***Abstract*:**

Nowadays, staying connected often means logging in instead of showing up. Because of apps and websites built for sharing,the shape of friendships bends differently than before. Talking face to face? That's rarer - typed messages flash across devices at all hours. Who we are,how we speak, what feels close - it shifts when most contact lives behind glass. Screens mediate trust, reshape honesty, blur where personality ends and performance begins.

Digital threads weave ties just as real, though stitched through code. Though online spaces letpeople link across continents fast, yet closeness sometimes fades behind screens. Still, real talk often gets lost even when chats pile up quickly. Questions grow around whether bonds stay genuine amid constant pings and updates. Some wonder if endless scrolling drains more than it gives back now. Probing deeper shows tools meant to unite can quietly isolate too. What feels like connection might just be noise dressed as conversation today.

INTRODUCTION

Nowadays people talk differently because the web and online apps changed everything. Not only do sites likeInstagram or LinkedIn help messages move fast, but also shape how bonds grow over time. Instead of just texting, folks now rely on WhatsApp or X to keep friendships alive across distances. Building ties online means more than sending notes - it involves showing up regularly in shared digital spots.

Back then, people met by being inthe same room, walking the same streets. Now screens bridge continents in seconds, linking lives that never cross paths in real life. Even so, while distance shrinks, something else stretches thin -

the way feelings are shown, heard, felt. Promises once sealed in person now float through signals, reshaped by speed and silence alike.

This study looks into virtual networking's impact on personal connections through social angles, then shifts to mental effects, followed by career-related changes instead.

NEED OF THE STUDY.

Connections online grow larger when people keep in touch digitally, often through loose links that bring ne w ideas, chances, or fresh viewpoints their way. Sometimes it's those distant contacts doing the most to open doors.

Information spreads faster this way, even if the bond feels thin. A message here, a comment there - small m oments add up to wider reach.

Diverse thoughts arrive more easily when networks stretch beyond close circles.Suddenly, screens allow qui ck messages and pictures to flow fast. Yet emotions shift when people stop meeting eyes. Texts replace talk s. Images fill silence.

Expression mutates without physical presence nearby. Tone changes. Reactions adapt slowly.

Faces often speak louder than words - without them, digital ties can feel hollow even when we're always onl ine. Missing gestures, tone shifts, silence shared between thoughts weakens how bonds grow deep.

Out there on screens, people shape their image carefully - this shifts how connections start, how they feel, th en stick around. What shows up in profiles colors every chat that follows. First impressions? They build slo wly now, through choices made long before a message is sent.

3.1Population and Sample

The study targets individuals between the ages of **18 and 35**, as this demographic represents the most active users of virtual networking platforms.

- **Sample Size:** 100–150 participants
- **Sampling Technique:** Convenience sampling
- **Location:** Urban and semi-urban areas

Participants were selected based on their regular use of platforms such as Instagram, WhatsApp, LinkedIn, and other social networking tools.

3.2 Data and Sources of Data

A structured questionnaire was designed to collect data on:

- Daily time spent on social media
- Number of online connections
- Perceived closeness of relationships
- Preference for online vs. offline communication

The survey included:

- Multiple-choice questions

- Likert scale statements (Strongly Agree to Strongly Disagree)

This method provided measurable data that could be analyzed statistically.

3.3 Theoretical framework

This study is grounded in several key sociological and communication theories that help explain the transformation of interpersonal relationships in the context of virtual networking.

1. Social Presence Theory

Social Presence Theory suggests that communication effectiveness depends on the ability of a medium to convey the presence of another person. Face-to-face communication has high social presence due to the availability of non-verbal cues, while digital communication has lower social presence.

In virtual networking:

- Lack of physical cues reduces emotional connection
- Interactions may feel less personal

2. Media Richness Theory

Media Richness Theory classifies communication channels based on their ability to convey information effectively.

- Rich media: Face-to-face interaction
- Lean media: Text messages and emails

Virtual networking often relies on lean media, which may limit the depth of communication.

3. Social Exchange Theory

This theory suggests that relationships are formed based on a cost-benefit analysis. Individuals seek relationships that provide maximum benefits with minimal costs.

In online interactions:

- Benefits include convenience and accessibility
- Costs include lack of authenticity and emotional depth

4. Hyperpersonal Communication Theory

Proposed by Walther, this theory explains how online communication can sometimes become more intimate than face-to-face interaction due to selective self-presentation.

People:

- Share more personal information
- Idealize others
- Form quick emotional connections

5. Symbolic Interactionism

This theory emphasizes how individuals create meaning through social interactions.

In virtual networking:

- Symbols such as emojis and likes replace traditional cues
- Meaning is constructed differently

RESEARCH METHODOLOGY

This study adopts a **mixed-method research design**, combining both quantitative and qualitative approaches to provide a comprehensive understanding of how virtual networking influences interpersonal relationships. The integration of numerical data with personal experiences allows for a more holistic interpretation of the research problem.

The quantitative component focuses on measurable variables such as frequency of social media usage, number of online connections, and perceived relationship strength. In contrast, the qualitative component explores individual experiences, emotional perceptions, and subjective interpretations of online interactions.

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For this study secondary data has been collected. From the website of KSE the monthly stock prices for the sample firms are obtained from Jan 2010 to Dec 2014. And from the website of SBP the data for the macroeconomic variables are collected for the period of five years. The time series monthly data is collected on stock prices for sample firmsand relative macroeconomic variables for the period of 5 years. The data collection period is ranging from January 2010 to Dec 2014. Monthly prices of KSE -100 Index is taken from yahoo finance.

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3.4Statistical tools and econometric models

This section elaborates the proper statistical/econometric/financial models which are being used to forward the study from data towards inferences. The detail of methodology is given as follows.

3.4.1 Descriptive Statistics

Descriptive Statics has been used to find the maximum, minimum, standard deviation, mean and normally distribution of the data of all the variables of the study. Normal distribution of data shows the sensitivity of the variables towards the periodic changes and speculation. When the data is not normally distributed it means that the data is sensitive towards periodic changes and speculations which create the chances of arbitrage and the investors have the chance to earn above the normal profit. But the assumption of the APT is that there should not be arbitrage in the market and the investors can earn only normal profit. Jarque bera test is used to test the normality of data.

3.4.2 Fama-Mcbeth two pass regression

After the test statistics the methodology is following the next step in order to test the asset pricing models. When testing asset pricing models related to risk premium on asset to their betas, the primary question of interest is whether the beta risk of particular factor is priced. Fama and McBeth(1973)develop a two pass methodology in which the beta of each asset with respect to a factor is estimated in a first pass time series regression and estimated betas are then used in second pass cross sectional regression to estimate the risk premium of the factor. According to Blum (1968) testing two-parameter models immediately presents an unavoidable errors-in-the variables problem.It is important to note that portfolios (rather than individual assets) are used for the reason of making the analysis statistically feasible.Fama McBeth regression is used to attenuate the problem of errors-in-variables (EIV) for two parameter models (Campbell, Lo and MacKinlay, 1997).If the errors are in the β (beta)of individual security are not perfectly positively correlated, the β of portfolios can be much more precise estimates of the true β (Blum, 1968).

The study follow Fama and McBeth two pass regressionto test these asset pricing models.The Durbin Watson is used to check serial correlation and measures the linear association between adjacent residuals from a regression model. If there is no serial correlation, the DW statistic will be around 2. The DW statistic will fall if there is positive serial correlation (in worst case, it will be near zero). If there is a negative correlation, thestatistic will lie somewhere between 2 and 4. Usually the limit for non-serial correlation is considered to be DW is from 1.8 to 2.2. A very strong positive serial correlation is considered at DW lower than 1.5 (Richardson and smith, 1993).

According to Richardson and smith(1993) to make the model more effective and efficient the selection criteria for the shares in the period are: Shares with no missing values in the period, Shares with adjusted R^2 < 0 or F significant (p-value) >0.05of the first pass regression of the excess returns on the market risk premium are excluded. And Shares are grouped by alphabetic order into group of 30 individual securities (Roll and Ross, 1980).

3.4.2.1 Model for CAPM

In first pass the linear regression is used to estimate beta which is the systematic risk.

$$R_i - R_f = (R_m - R_f)\beta \qquad (3.1)$$

Where $R_i$isMonthly return of thesecurity, R_f isMonthly risk free rate, R_m isMonthly return of market and βis systematic risk (market risk).

The excess returns R_i - R_f of each security is estimated from a time series share prices of KSE-100 index listed shares for each period under consideration. And for the same periodthe market Premium R_m - $R_f$also estimated. After that regress the excess returns R_i - R_f on the market premium R_m - $R_f$to find the beta coefficient (systematic risk).

Then a cross sectional regression or second pass regression is used on average excess returns of the shares and estimated betas.

$$\hat{R}_i = \gamma_0 + \gamma_1\beta_1 + \epsilon \qquad (3.2)$$

Where $ƛ_0$= intercept, $\hat{R}_I$is average excess returns of security i,$\beta_I$isestimated be coefficient of security I and Є is error term.

3.4.2.2 Model for APT

In first pass the betas coefficients are computed by using regression.

$$R_i - R_f = \beta_i f_1 + \beta_{i2} f_2 + \beta_{i3} f_3 + \beta_{i4} f_4 + \epsilon \qquad (3.3)$$

Where Ri is the monthly return of stock i,R_f is risk free rate, β_i is the sensitivity of stock i with factors and ϵ is the error term.

Then a cross sectional regression or second pass regression is used on average excess returns of the shares on the factor scores.

$$\hat{R} = \gamma_0 + \gamma_1\beta_1 + \gamma_2\beta_2 + \gamma_3\beta_3 + \gamma_4\beta_4 + \epsilon_i \qquad (3.4)$$

WhereR̂ is average monthly excess return of stock I, ƛ = risk premium, β_1 to β_4 are the factors scores and ε_i is the error term.

3.4.3 Comparison of the Models

The next step of the study is to compare these competing models to evaluate that which one of these models is more supported by data.This study follows the methods used by Chen (1983), the Davidson and Mackinnon equation (1981) and the posterior odds ratio (Zellner, 1979) for comparison of these Models.

3.4.3.1 Davidson and MacKinnon Equation

CAPM is considered the particular or strictly case of APT. These two models are non-nested because by imposing a set of linear restrictions on the parameters the APT cannot be reduced to CAPM. In other words the models do not have any common variable. Davidson and MacKinnon (1981) suggested the method to compare non-nested models. The study used the Davidson and MacKinnon equation (1981) to compare CAPM and APT.

This equation is as follows;

$$R_i = \alpha R_{APT} + (1-\alpha)R_{CAPM} + e_i \qquad (3.5)$$

Where$R_{i=}$ the average monthly excess returns of the stock i, $R_{APT=}$ expected excess returns estimated by APT, $R_{CAPM=}$ expected excess returns estimated by CAPM and α measure the effectiveness of the models. The APT is the accurate model to forecast the returns of the stocks as compare to CAPMif α is close to 1.

3.4.3.2 Posterior Odds Ratio

A standard assumption in theoretical and empirical research in finance is that relevant variables (e.g stock returns) have multivariate normal distributions (Richardson and smith, 1993). Given the assumptionthat the residuals of the cross-sectional regression of the CAPM and the APT satisfy the IID (Independently and identically distribution) multivariate normal assumption (Campbell, Lo and MacKinlay, 1997), it is possible to calculate the posterior odds ratio between the two models.In general the posterior odds ratio is a more formal technique as compare to DM equation and has sounder theoretical grounds (Aggelidis and Maditinos, 2006).

The second comparison is done using posterior odd radio. The formula for posterior odds is given by Zellner (1979) in favor of model 0 over model 1.

The formula has the following form;

$$R = [ESS_0/ESS_1]^{N/2} N^{K_0-K_1/2} \qquad (3.6)$$

WhereESS_0iserror sum of squares of APT, ESS_1iserror sum of squares of CAPM, Nisnumber of observations, $K_0$is number of independent variables of the APT and K_1 isnumber of independent variables of the CAPM.As according to the ratio when;

R> 1 means CAPM is more strongly supported by data under consideration than APT.

R < 1 means APT is more strongly supported by data under consideration than CAPM.

IV. RESULTS AND DISCUSSION

More links online might mean a bigger circle of contacts. Still, quantity rarely brings real warmth between p eople.

Folks seem to find more chances to connect, be seen, get involved - thanks to online tools shaping how wor k ties form. Yet on the flipside, some say they feel stronger but also worn out by constant screen presence.

What shows up online often isn't the whole story - people highlight bits they want seen. Because of that, im pressions shift toward something polished, even if it doesn't match real life. Moments get shaped before sha ring, leading others to compare themselves to versions that feel out of reach.

Surprisingly, tightest bonds showed up in people mixing web chats with face-to-face talks. Not one replacing the other - instead, digital links seem to build alongside real-world contact.

Looking back, it becomes clear how online connections mix with face-to-face moments to form new kinds of interactions. Instead of staying separate, these spaces blend in ways that change how people relate. What once felt distinct now overlaps more than we might expect. Through screen based ties, a different rhythm of contact emerges alongside realworld meetings. These shifts don't erase older patterns - they reshape them quietly over time.

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