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# Online shopping behaviour on social media platforms from the perspective of trust and flow experience: a SEM-Neural Network Modeling

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ABSTRACT

*This study aims to examine online shopping behaviour on social media platforms. This study formulates a research model integrating trust with the flow theory and some basic constructs of the UTAUT. To analyze the data from an online survey involving 305 participants actively making online purchases through social media platforms. This study applied the Structural Equation Modeling-Artificial Neural Networks (SEM-ANN) technique. Incorporating statistically significant SEM findings, the ANN model was used to analyze linear and nonlinear interactions among proposed variables. The research findings demonstrate that flow emerges as the most significant determinant, succeeded by effort expectancy, social influence, and performance expectancy, in defining the concept of trust. However, the sensitivity analysis using ANN indicates that effort expectancy is the most important factor in establishing trust, followed by flow, social influence, and performance expectancy. The predictive power of intention to use is noteworthy in determining actual use behaviour, with trust and flow emerging as influential factors favourably impacting this intention.*



## Introduction

In the last few decades, social media has revolutionarily transformed how people communicate and behave as consumers (Edwards, 2011; Mir & Zaheer, 2012). The phrase "social media" includes Facebook, Snapchat, Twitter, Google+, LinkedIn, MySpace, YouTube, Flickr, etc. Such platforms allow customers to communicate knowledge and experience worldwide regarding different goods and services (Heinrichs et al., 2011; Rathore et al., 2016).

Consumers are perpetually and behaviourally engaged and spend time on social media ( Kim & Kim, 2018). Social media use for shopping has become a trend (Permatasari & Kartikowati, 2018). Consumers rely less on radio, television, magazines, and newspapers for product and service information and more on social media platforms (Mangold & Faulds, 2009). Thus, to reach this huge customer base and build a profitable relationship with them, business organizations have started thinking and designing ways of conducting business using social media platforms on e-commerce ( Kamboj et al., 2018). In a global range, businesses promote their owned social media groups or intermediaries' pages. By using social media, businesses can engage in a cost-effective mode of communication that enables direct interaction with their consumers (Kaplan & Haenlein, 2010; Swani et al., 2017). So, businesses are adopting social media-based advertising rapidly to reach customers and enhance their brand images. Besides, innovative products and services can be designed with the involvement and support of customers habituated to social media (Carlson et al., 2018; Kao et al., 2016). Moreover, businesses based on social media are blessed with various merits such as virtually 24/7 easy-doing business,

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improvement of consumer-business relationships, viral dissemination of products' and services' information, and so on (Bernoff & Li, n.d.; Chung & Austria, 2012; Kaplan & Haenlein, 2010). Along with the business practitioners, researchers and academics were spotlighted on social media-based online shopping to improve this platform and ensure full benefits for all the stakeholders.

Many scholars have studied different aspects of social media usage for online shopping. Some researchers attempted to find the motivating factors of online purchases on social media. Studying 315 social media users in Mauritius, Ramlugun and Jugurnauth (2014) identified that cost-saving, socializing, convenience, and trend discovery encourage consumers to browse and buy through social media (Ramlugun & Jugurnauth, 2014). Dependency on social media and perceived value were recognized as determinants of online shopping on social media in Indonesia (Permatasari & Kuswadi, 2017). Social media-based customer reviews, content users, and firms influence purchase decisions (International et al., 2019). A study of over 430 respondents in China found that social platform interactivity in content usefulness, real-time communication, stakeholders' communication, and engagement (Hussain et al., 2021). According to Chen (2014), speed, sociability, connectedness, dependency, and low perceived risk are major decision-driving issues for online shopping through social media. Besides, information quality about products and services and page service quality in social media were considered (Huang & Benyoucef, 2013; Nadeem et al., 2015). Online purchase intention is influenced by how often and long one uses social network services (Arceo et al., 2018). Still, many factors, such as enjoyment, engagement, trust, and influence from others, needed to be investigated and explored from the social shopping perspective. Furthermore, most of the studies have been done in developed countries, and little can be found in developing economies like Bangladesh.

Although mentionable, researchers have conducted studies on consumer use intention rather than actual shopping behaviour (Fogel & Zachariah, 2017; Wei et al., 2018). As shopping intention does not represent actual shopping behaviour, it is important to study the actual behaviour (Reza et al., 2012). Consumers have the possibility of wrongly predicting their intentions (Auger & Devinney, 2007). Changes or distractions in online shopping arrangements and lack of shopping environment availability negatively impact actual use behaviour (Asiedu & Dube, 2020; Carrington et al., 2010). According to Foxall (2015), consumer behaviour is considered a complicated area of study because the absolute prediction of human behaviour is not easy. We aimed to examine the key determinants of consumers' intention to make online purchases and their subsequent actual purchasing behaviour on social network sites.

The extant research on online shopping behaviour through social media has investigated from different behavioural perspectives, such as the perceived value aspect (Hu et al., 2016; Wei et al., 2018), technological view (Gibreel et al., 2018; Huang & Benyoucef, 2017), privacy concerns (Wang & Hu, 2009), branding and co-creation issue (Kamboj et al., 2018), gender and generation impacts (Nadeem et al., 2015) and so forth. However, these prior studies have only counted the influence of online social consumers' cognitive views and ignored the emotional views, such as flow experience, which determine the optimal user experience (Pelet et al., 2017a). Flow experience involves users heavily with anything and cannot pay attention to the change in time and even their surroundings (Csikszentmihalyi, 1990). Previous research works argued that people become fully engaged in social media and do online shopping with full enjoyment and concentration (Gao & Bai, 2014). Considering this flow effect, researchers conducted various studies in the information systems context (Guo & Poole, 2009; Koufaris, 2002; Wu et al., 2020; Korzaan, 2003; Mahnke et al., 2015). Indeed, flow experience increases social media use frequency and duration (Pelet et al., 2017a), which supports social commerce (Zhang et al., 2014). Social commerce researchers explored how interpersonal characteristics, including perceived knowledge, familiarity, and resemblance, affect online purchase flow experience (Liu et al., 2016). Zhou (2019) also examines how human-human and human-computer interactions affect the flow and intention to purchase social media. There is little study in Bangladesh on the impact of flow experience on online purchase intent and usage behaviour, especially regarding new technology acceptance characteristics, including performance expectancy, effort expectancy, and social influence. To fill the literature gap, this study presents a theoretical framework that blends the fundamental components of the (UTAUT) model with flow experience. This study examines how technological acceptability factors, particularly flow experience, affect people's desire to buy socially and their actual use of social shopping platforms. Research questions:

i. What are the key factors that influence customers' online shopping and actual shopping using social media?
ii. How does flow experience influence online shopping intention and actual buying behaviour?
iii. What are the more crucial determinants of fostering social media-based online shopping?

## Literature Review

### Theoretical Framework and Hypothesis

Researchers in the field of information systems have done a range of studies to gain insight into the motivations behind individuals' use of new information systems. Two major groups emerged from these research works. The goal of adopting cutting-edge technology is the subject of one set of studies where others assess the success of information systems at both individual and organizational levels (Compeau & Higgins, 1995; Goodhue & Thompson, 1995).

Various theoretical frameworks have been developed and employed to assess the uptake of advanced technologies. The study incorporates various frameworks, including the theory of planned behaviour (TPB), theory of innovation adoption, theory of innovation diffusion, theory of reasoned action, motivational model, technology acceptance model (TAM), combined TAM and TPB (C-TAM-TPB), model of personal computer utilization, and social cognitive theory (Venkatesh et al., 2003). The authors formulated a fundamental theoretical framework called the Unified Theory of Acceptance and Use of Technology (Venkatesh et al., 2003). The framework effectively incorporated eight pre-existing theories and showed improved predictive capability when compared to the separate models. The current model explains 70% of behavioural intention variance and 50% of use behaviour variation. Venkatesh et al. (2003) examined the UTAUT paradigm. The project collected primary data from four organizations. The model's validity was strengthened by adding data from two more organizations, providing strong empirical evidence for the UTUAT. This methodology has been used to study technology adoption in Internet banking, mobile payment, mHealth, and mobile apps. Scholarly empirical investigations (Hoque & Sorwar, 2017; Rahi et al., 2019; Al-Saedi, 2020) support this assumption.

E-commerce platform adoption and use depend on trust in the UTAUT model (Beyari & Ghouth, 2018). Nel and Boshoff (2017) found that trust affects app-based mobile service use. In human-computer interaction, flow theory has been widely investigated in online platform adoption and use (Hsu et al., 2017; Huang, 2006). Flow experience boosts online clients' confidence (Wang and Hu., 2009). Researchers found online flow experience lowers technology avoidance and negative views. Thus, the researchers evaluated UTAUT, trust, and flow literature.

A theoretical framework is used to research online purchase behaviour on social media. The three basic elements of the widely used UTAUT model in academic research are included in this study, along with trust and flow theories. The theoretical research model is shown in Figure 1. Performance expectation (PE), effort expectation (EE), and social influence (SI) are thought to influence trust. Trust and flow are known to influence a person's decision to use a product or service. Studies show that online customers' social media intentions influence their behaviour. Next, we'll explain the study's hypothesis, empirical findings, and conclusion.

**Effort Expectancy**

Effort Expectancy (EE) is the level of comfortability and easiness of utilizing a particular system (Venkatesh et al., 2003). Additionally, EE is an individual's perception of a system's usage without the need for substantial ( Davis,1989). We define EE as how participants view online shopping using social networking platforms as effortless and user-friendly.

When individuals see that a particular system is difficult to use, there is less chance of it being considered a pleasant system (Moon & Kim, 2001). Besides, Zhou (2013) mentioned in his research work that perceived EE helps increase people's feelings and allows them to get a flow experience. When people realize the difficulty of a specific system, they may think that businesses did not invest efforts and resources to make that system more convenient to use, which may reduce trust in it (Zhou, 2014). Researchers also recognized in their study that PE significantly predicts Facebook users' trust (Lankton & McKnight, 2011). Besides, a study of users' trust in social network services found a correlation between EE and trust (Chang et al., 2017). Accordingly, we develop the following hypotheses:

*H1: There is a positive relationship between effort expectancy and flow.*

*H2: There is a positive relationship between effort expectancy and trust.*

**Performance Expectancy**

Performance Expectancy (PE) is the idea that employing a particular method enhances productivity at work (Venkatesh et al., 2003). It is a person's conviction that using a system will improve their ability to accomplish their work (Davis, 1989). PE in this study stands for performance expectancy, which measures how much respondents think social networking sites for online buying would enhance the performance of shopping activities.

The point when people believe that the greater operational efficiency of a website will result in increased initial trust (Zhou, 2014). Besides, Zhu et al. (2003) suggested that perceived usefulness is a crucial element in predicting m-trust. Furthermore, a study of Fashion brands on retail websites has identified that PE positively influences trust (Loureiro et al., 2018). Accordingly, we develop the following hypothesis:

*H3: There is a positive relationship between performance expectancy and trust.*

**Social Influence**

Social influence (SI) measures an individual's perception of influential people's support for a new system (Venkatesh et al., 2003). Ajzen (1991) defined subjective norm as "the perceived influence from society to either engage in or refrain from a particular behaviour." We define SI as the degree to which individuals perceive that important figures endorse the usage of social media for accomplishing their purchase activities.

When a prominent individual utilizes specific mobile banking services, this occurrence fosters confidence among their associates or supporters (Khasawneh et al., 2018). In addition, an individual's faith in an autonomous vehicle may be influenced by the positive attitudes of others towards it (Zhang et al., 2020). Moreover, research on the adoption of electronic government services has found that SI has a crucial role in influencing trust in the Internet (Mensah, 2019). In addition, Li et al. (2008) said that social impact has a more prominent role in the initial formation of trust compared to cognitive or personality characteristics. Accordingly, we develop the following hypothesis:

*H4: There is a positive relationship between social influence and trust.*

**Flow**

According to Csíkszentmihályi & Csikszentmihalyi (1992), flow is the enjoyable sensation of being fully engaged in an activity. Chang and Zhu (2012) defined flow as the overall experience of using social media platforms. In this study, flow is the amount to which social media shoppers have good encounters.

The flow theory is commonly used to analyze the behaviour of users in various domains of technologically-mediated situations (Hoffman & Novak, 1996). Flow can produce trust, and flow experience in the online environment can minimize unwanted circumstances, ultimately building trust in the customers' minds (Bilgihan, 2016). Besides, customers' experience with the organization's website may prompt trust-building. Furthermore, Chang (2014) studied tourist guide performance and found that flow experience positively influences benevolence and trust. In addition, in the context of tourism, Chang (2014) mentioned that tourists do not want to participate in shopping activities if they do not feel the trip is enjoyable. Also, flow experience was suggested as an important factor in interpreting users' future online behaviour (M.-C. et al., 2010). Zhou (2019) mentioned that when users are in a flow state in the social commerce platforms, they feel enjoyment, resulting in positive social purchase intention. Accordingly, the following hypotheses are proposed:

*H5: There is a positive relationship between flow and trust.*

*H6: There is a positive relationship between flow and intention to use.*

**Trust**

Trust is an individual's perception that another person's actions and statements are reliable and that they possess positive intentions to fulfil their commitments (Bligh, 2017). Previous researchers mentioned trust as the belief that second parties will remain faithful to their commitments (Lu et al., 2011). This study uses the term "trust" to denote the extent to which participants hold the belief that online sellers operating on social media platforms fulfil their commitments.

Trust significantly and positively influences usage intention as it ensures that customers will get positive yields later on (Zhou, 2012). Also, earlier researchers recognized that the absence of trust would prevent buyers from participating in online transactions, which is the main obstacle to e-commerce adoption (Jarvenpaa et al., 2006). Besides, a study of buying decisions on mobile apps identified that trust significantly impacts buying intention (Chandra et al., 2019). Additionally, trust predicts behavioral intention (Chandra et al., 2010; Shin, 2010). Given this, the following hypothesis is proposed:

*H7: There is a positive relationship between trust and intention to use.*

**Intention to use**

Intention to Use (IU) figures out how likely people are to do what they want to do (Fishbein & Ajzen, 1975). Venkatesh et al. (2003) showed that the IU explains differences in UB when it comes to technology in a big way. Alalwan et al. (2017), who studied the use of mobile banking in Jordan, also found that people's willingness to use a system was a good indicator of how they used mobile banking services. Also, past researchers have shown that IU and UB are related in a good way (Venkatesh & Davis, 2000). Consequently, we propose that:

*H8: There is a positive relationship between intention to use and use behaviour*

## Research and Methodology

**Measurement Instruments**

All measuring items used to assess constructs in the research model were chosen from existing literature to ensure their suitability. The predictor variables consist of performance expectancy, measured by three items; effort expectancy, measured by four items; and social influence, measured by four items. These measurements were obtained from the studies conducted by Celik (2016), Liebana-Cabanillas and Alonso-Dos-Santos (2017), Sharifi fard et al. (2016), and Venkatesh et al. (2003). Four measurement items drawn from the studies of Hsu et al. (2017) and Bilgihan (2016) make up the Flow construct. Three measurement items that make up the Trust construct were taken from Blanche et al. (2012) and Gefen & Straub (2003). Three and four items, respectively, make up the outcome variables for use behaviour and intention to use. They are taken from Celik (2016), Liebana-Cabanillas & Alonso-Dos-Santos (2017), Sharifi fard et al. (2016), and Venkatesh et al. (2003).

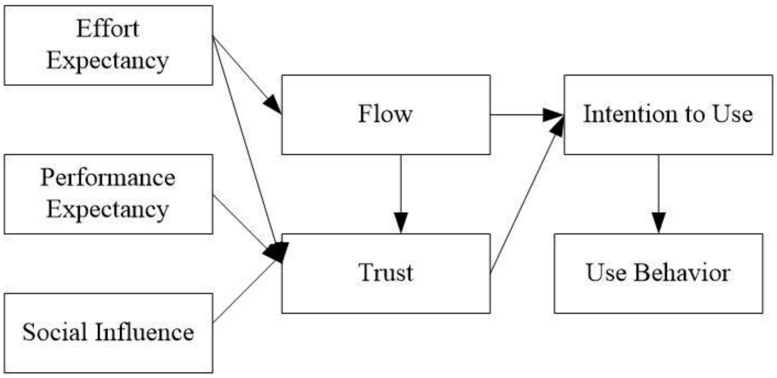


**Figure 1:** Research Model

**Questionnaire Design and Data Collection**

This study used an online survey for data. Twenty-five measurement items were used. Google Form links of a structured questionnaire were delivered via Facebook and email. The survey ran from August 1 to 30, 2023. The questionnaire was developed in English because its target respondents can understand the basics of English. Three sections comprised the questionnaire. We briefly explained the study's goals and assured participants that answers would be kept confidential. Participants were asked basic demographic questions in Section B. Section C contains the suggested study model's latent construct quantification questions. The measurement questions were scored on a 5-point Likert scale from "strongly disagree" to "strongly agree". Three experienced researchers checked the survey questions for uniformity, clarity, and participant instructions. To test the survey's applicability, 20 target demographic members participated in a pilot research. Expert researchers' recommendations and pilot study data were used to improve formatting, questionnaire order, and item legibility. Bangladeshi social media users were the target population. A convenience sampling method collected empirical data. Kline (2023) recommends testing a structural equation model with 200–300 samples. Hair et al. (2019) recommend five observations per independent variable and ten replies. The independent and mediating factors in this study were measured with 25 items. This study is statistically significant, with 250 participants. After eliminating missing responses, 305 samples were analyzed.

**Analysis**

Structural equation modelling (SEM) validates a theory and simulates linear relationships among constructs. SEM, however, oversimplifies the complexities people confront when making judgments about online shopping on social networking sites. ANN is capable of detecting nonlinear as well as linear associations between variables through its modelling. However, this 'Black Box' approach is unsuitable for theory testing (Hew et al., 2016). Therefore, we used the two-staged SEM-ANN method to examine the proposed research model for online shopping behaviour on social media platforms. Several researchers have used this two-staged SEM-ANN approach to solve their research problems (Leong et al., 2019; Li et al., 2008)

## Results

**Demographic Information**

Table 1 depicts that most of the respondents (79 percent) were between the ages of 20 and 29. The majority of respondents (65%) are male, while female respondents make up 35%. Also, Table 1 shows most of the respondents are single (71 percent), while 29 percent were married. Furthermore, the proportion of bachelor's and master's degree holders is close (52:45). Table 1 also reveals that more than 40 percent of respondents belong to the income group of less than BDT 5000, as 69 percent of the respondents are students. The remaining respondents are service holders.

**Table 1**: Demographic Information

| **Items** | | **Frequency** | **Percentage** |
|---|---|---|---|
| **Age** | Under 20 | 14 | 5.00 |
| | 20-24 | 146 | 48.00 |
| | 25-29 | 95 | 31.00 |
| | 30-34 | 38 | 12.00 |
| | Above 34 | 12 | 4.00 |
| **Gender** | Male | 199 | 65.00 |
| | Female | 106 | 35.00 |
| **Marital Status** | Single | 218 | 71.00 |
| | Married | 87 | 29.00 |
| **Education Level** | Bachelors | 160 | 52.00 |
| | Masters | 136 | 45.00 |
| | PhD | 9 | 3.00 |
| **Income (Monthly)** | No Income | 33 | 11.00 |
| | Below BDT 5,000 | 125 | 41.00 |
| | BDT 5,001-BDT 10,000 | 32 | 10.00 |
| | BDT 10,001-BDT 20,000 | 17 | 5.00 |
| | BDT 20,001-BDT 30,000 | 13 | 4.00 |
| | BDT 30,001-BDT 40,000 | 29 | 10.00 |
| | BDT 40,001-BDT 50,000 | 15 | 5.00 |
| | BDT 50,001-BDT 60,000 | 20 | 7.00 |
| | Above BDT 60,000 | 21 | 7.00 |
| **Occupation** | Service Holder | 95 | 31.00 |
| | Student | 210 | 69.00 |

### Common Method Bias and Multicollinearity Test

Following Podsakoff et al. (2003), we tested common method bias (CMB). As Podsakoff et al. (2003) stated, CMB may be problematic when one factor explains most of the variance. To discover the major component explaining variation, we used principal axis factoring (PAF) analysis. Podsakoff et al. (2003) found that a single component can only explain 30.695 percent of the variation, well below the necessary 50%. We assessed the CMB using the variance inflation factor (VIF). According to O'Brien (2007), VIF should be below 3.30. This study effort is risk-free for CMB. O'Brien (2007) also claimed that VIF values above 10 indicate multicollinearity. Table 2 data indicate that this research is multicollinearity-free.

**Table 2:** Collinearity Statistics (VIF)

| **Constructs** | **EE** | **FL** | **IU** | **PE** | **SI** | **TR** | **UB** |
|---|---|---|---|---|---|---|---|
| **EE** | | 1.000 | | | | 1.751 | |
| **FL** | | | 1.345 | | | 1.433 | |
| **IU** | | | | | | | 1.000 |
| **PE** | | | | | | 1.707 | |
| **SI** | | | | | | 1.601 | |
| **TR** | | | 1.345 | | | | |
| **UB** | | | | | | | |

**Note:** PE: performance expectancy; EE: effort expectancy; SI: social influence; FL: flow; TR: Trust; IU: intention to use; UB: use behaviour

**Measurement Model**

Measurement methods assess construct reliability, indicator convergent, and discriminant validity. Exploratory research should have 0.60 reliability, while known measurement items should have 0.70 (Podsakoff et al., 2003). Composite reliability (CR) and Cronbach's alpha measure internal consistency. Except for performance expectancy, Table 3's Cronbach's alpha and CR scores are above the threshold. Cronbach's alpha for performance expectancy is close to the threshold. Thus, we consider this construct. The CR and AVE performance expectancies exceed the requirements. To ensure indicator reliability, factor loading should surpass 0.70. Table 3 demonstrates that most item loadings above 0.70, except for EE1 (0.671) and UB3 (0.678), indicate strong indicator reliability. Evaluate convergent validity with extracted average variance. All constructs in Table 3 have AVE values above 0.50, proving convergent validity. Table 3 also demonstrates that CR (0.797–0.933) and AVE (0.555–0.823) met the criterion. Table 3 shows composite reliability (CR) confidence ranges of 0.797 to 0.933 and AVE of 0.555 to 0.823. Table 3's constructs are convergent since these values meet the threshold. Convergent validity is confirmed by AVE values ≥ 0.50 for all Table 3 constructs. It shows good internal consistency and convergent validity of the measurement tool. Hensel, Hubona, and Ray (2016) analyze discriminant validity by determining the square root of the average variance extracted (AVE) for each construct and assessing its correlations with others. Table 4 demonstrates that AVE has bigger estimated square roots than other structures. Significant evidence supports AVE's discriminant validity. Table 6 reveals that all HTMT values were < 0.85 (Kline, 2015). Therefore, these values indicate strong discriminant validity.

**Table 3:** Measurement Model

| Constructs | Items | Loadings | Cronbach's alpha | CR | AVE |
|---|---|---|---|---|---|
| **Effort Expectancy (EE)** | **EE1** | **0.671** | **0.744** | **0.840** | **0.569** |
| | **EE2** | **0.847** | | | |
| | **EE3** | **0.766** | | | |
| | **EE4** | **0.723** | | | |
| **Performance Expectancy (PE)** | **PE1** | **0.790** | **0.685** | **0.825** | **0.611** |
| | **PE2** | **0.776** | | | |
| | **PE3** | **0.780** | | | |
| **Social Influence (SI)** | **SI1** | **0.825** | **0.844** | **0.895** | **0.682** |
| | **SI2** | **0.851** | | | |
| | **SI3** | **0.858** | | | |
| | **SI4** | **0.766** | | | |
| **Flow (FL)** | **FL1** | **0.780** | **0.729** | **0.846** | **0.647** |
| | **FL2** | **0.756** | | | |
| | **FL3** | **0.871** | | | |
| **Trust(TR)** | **TR1** | **0.901** | **0.797** | **0.882** | **0.715** |
| | **TR2** | **0.738** | | | |
| | **TR3** | **0.887** | | | |
| **Intention to Use(IU)** | **IU1** | **0.809** | **0.818** | **0.892** | **0.734** |
| | **IU2** | **0.877** | | | |
| | **IU3** | **0.884** | | | |
| **Use Behavior (UB)** | **UB1** | **0.791** | **0.773** | **0.853** | **0.594** |
| | **UB2** | **0.842** | | | |
| | **UB3** | **0.678** | | | |
| | **UB4** | **0.764** | | | |

**Note:** AVE = average variance extracted; CR = composite reliability

**Table 4:** Correlation matrix and square root of the AVE

| Constructs | EE | FL | IU | PE | SI | TR | UB |
|---|---|---|---|---|---|---|---|
| **EE** | **0.754** | | | | | | |
| **FL** | 0.426 | **0.804** | | | | | |
| **IU** | 0.580 | 0.599 | **0.857** | | | | |
| **PE** | 0.602 | 0.381 | 0.462 | **0.782** | | | |
| **SI** | 0.481 | 0.504 | 0.569 | 0.482 | **0.826** | | |
| **TR** | 0.485 | 0.506 | 0.528 | 0.457 | 0.481 | **0.846** | |
| **UB** | 0.538 | 0.603 | 0.647 | 0.428 | 0.559 | 0.530 | **0.771** |

**Note:** PE: performance expectancy; EE: effort expectancy; SI: social influence; FL: flow; TR: Trust; IU: intention to use; UB: use behaviour

**Table 5:** Heterotrait-Monotrait Ratio

| Constructs | EE | FL | IU | PE | SI | TR | UB |
|---|---|---|---|---|---|---|---|
| **EE** | | | | | | | |
| **FL** | 0.563 | | | | | | |
| **IU** | 0.743 | 0.770 | | | | | |
| **PE** | 0.846 | 0.523 | 0.616 | | | | |
| **SI** | 0.606 | 0.634 | 0.686 | 0.629 | | | |
| **TR** | 0.619 | 0.652 | 0.646 | 0.604 | 0.584 | | |
| **UB** | 0.685 | 0.784 | 0.797 | 0.580 | 0.681 | 0.674 | |

**Note:** PE: performance expectancy; EE: effort expectancy; SI: social influence; FL: flow; TR: Trust; IU: intention to use; UB: use behaviour

**Structural Model**

A structural model can be used to evaluate how the many constructs in the theoretical model relate to one another. The statistical hypotheses in this investigation were examined at the 5% significance level. Through the use of bootstrapping, the hypotheses were assessed. Utilizing t-statistics and the path coefficient (β), the link between the independent and dependent variables was investigated. The path coefficient (β), t-statistics, p-value, and the status of each hypothesis are mentioned in Table 6 as a consequence of the direct path hypotheses. The findings show that there were significant relationships between the following: EE and FL (β = 0.426; t-statistics = 7.815; p-value = 0.00), EE and TR ( = 0.191; t-statistics = 2.758; p-value = 0.006), PE and TR (β = 0.151; t-statistics = 2.280; p-value = 0.023), SI and TR (β = 0.177; t-statistics = 3.021; p-value = 0.003), FL and TR (β = 0.278; t-statistics = 4.880; p-value = 0.000), FL and IU (β = 0.447; t-statistics = 7.867; p-value = 0.000), TR and IU (β = 0.302; t-statistics = 5.980; p-value = 0.000), and IU and UB (β = 0.647; t-statistics = 18.636; p-value = 0.000). It was concluded that all the hypotheses were supported.

**Table 6:** Structural Model

| Path | B | t- Statistics | p-Value | Comments |
|---|---|---|---|---|
| **H1:EE→FL** | 0.426 | 7.815 | 0.000 | Supported |
| **H2:EE→TR** | O.191 | 2.758 | 0.006 | Supported |
| **H3: PE→TR** | 0.151 | 2.280 | 0.023 | Supported |
| **H4:SI→TR** | 0.177 | 3.021 | 0.003 | Supported |
| **H5: FL→TR** | 0.278 | 4.880 | 0.000 | Supported |
| **H6: FL→IU** | 0.447 | 7.867 | 0.000 | Supported |
| **H7: TR→IU** | 0.302 | 5.980 | 0.000 | Supported |
| **H8: IU→UB** | 0.647 | 18.636 | 0.000 | Supported |

**Note**: Significant at $p < 0.05$; PE: performance expectancy; EE: effort expectancy; SI: social influence; FL: flow; TR: Trust IU: intention to use; UB: use behavior

**Predictive Relevance**

Stone-Geisser's $Q^2$ method was used to assess endogenous variables' predictive power (Geisser, 1974). Hair et al. (2019) classify $Q^2$ values of 0.02, 0.15, and 0.35 as low, moderate, and high predictive importance. Table 7 shows that all endogenous constructs except flow (0.107) had positive $Q^2$ values over 0.15, indicating predictive relevance. $R^2$ shows endogenous variable predictive power. The model's $R^2$ values of 0.181, 0.388, 0.427, and 0.418 for FL, TR, IU, and UB demonstrate its great explanatory power.

**Table 7:** Predictive Relevance

| Constructs | R Square | Q Square |
|---|---|---|
| **FL** | **0.181** | **0.107** |
| **TR** | **0.388** | **0.253** |
| **IU** | **0.427** | **0.297** |
| **UB** | **0.418** | **0.231** |

**Note:** FL: flow; TR: Trust; IU: intention to use; UB: use behavior

**Effect size**

The predictive power of exogenous factors is quantified by the effect size. The effect size of exogenous factors was determined using $f^2$. High, medium, and low effect sizes are indicated by $f^2$ values of 0.35, 0.10, and 0.02 (Cohen, 2013). Table 8 shows the effect size, meaning that all exogenous variable $f^2$ values were positive and more than 0.02. Consequently, the endogenous variables were impacted by all exogenous factors. Additionally, the effect sizes ($f^2$ values) for flow and trust about use intention indicate that flow has a greater impact on use intention than trust. Moreover, the flow has the highest impact on trust-building.

**Table 8:** Effect size

| Constructs | EE | FL | IU | PE | SI | TR | UB |
|---|---|---|---|---|---|---|---|
| **EE** | | 0.221 | | | | 0.034 | |
| **FL** | | | 0.259 | | | 0.088 | |
| **IU** | | | | | | | 0.719 |
| **PE** | | | | | | 0.022 | |
| **SI** | | | | | | 0.032 | |
| **TR** | | | 0.118 | | | | |
| **UB** | | | | | | | |

**Note**: Significant at $p < 0.05$; PE: performance expectancy; EE: effort expectancy; SI: social influence; FL: flow; TR: Trust IU: intention to use; UB: use behavior

**Importance-Performance Map Analysis**

In 1977, Martilla and James discovered IPMA. IPMA extends PLS-SEM by demonstrating how independent factors affect the dependent variable (Streukens et al., 2017). This evaluation seeks to identify high-priority constructs with poor performance. Managers may use this analysis to prioritize drivers to achieve a higher level of a target variable of interest. The responsible authority may make decisions based on two dimensions (performance and significance) and make necessary changes. Trust is more important in use behaviour, but it has a low performance. As a result, we need to focus here on improving this dimension. Besides, the flow has greater importance than effort expectancy, but effort expectancy performs better than the flow. As a result, since respondents prioritize this construct, concerned people should concentrate on it to enhance its performance.

**Table 9:** Importance-Performance Map Analysis

| Latent Constructs | Construct Total Effect | Construct Performance |
|---|---|---|
| **EE** | 0.210 | 71.450 |
| **PE** | 0.033 | 72.454 |
| **SI** | 0.036 | 64.574 |
| **FL** | 0.373 | 70.796 |
| **TR** | 0.192 | 57.583 |
| **IU** | 0.714 | 70.798 |

**Note:** EE: effort expectancy; PE: performance expectancy; SI: social influence; FL: flow; TR: Trust IU: intention to use

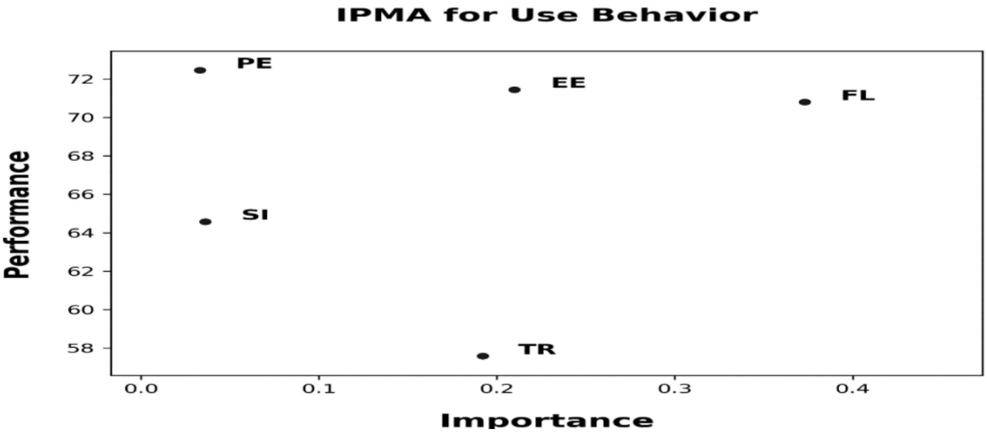


**Figure 2:** Importance performance map analysis (IPMA)

## Neural Network Analysis

Since SEM and MRA can only investigate linear correlations, Chan & Chong (2012), Sim et al. (2014), and Tan et al. (2014) suggest simplifying the complex decision-making process. The artificial neural network (ANN) model may correlate independent and dependent variables linearly and nonlinearly (Chan & Chong, 2012). Artificial neural networks (ANN) can disclose linear and nonlinear patterns without a theoretical underpinning, but their opaque "black-box" activities make them unsuitable for hypothesis testing or causal relationship research (Chan & Chong, 2012). Researchers chose an integrated SEM-ANN approach to incorporate the benefits of both. The SEM-ANN method has two phases. Structural Equation Modelling (SEM) can assess the study model's comprehensiveness and identify statistically important drivers. To decide the importance, the neural network model receives these predictors.

To simulate the human brain, the ANN has many interconnected processing units or artificial neurons (Tsoukalas & Uhrig, 1997). ANN is a complex analytical technique with higher accuracy than statistics (Chong, 2013). ANNs have input, hidden, and output layers. ANN models include feedforward neural networks, recurrent networks, radial basis function networks, and multi-layer perceptrons (Sim et al., 2014). This study used multi-layer perceptrons. SPSS 21 implemented the neural network model. Smart-PLS output predictors with statistical significance were neural model inputs. Input layer nodes equal Smart-PLS output statistically significant predictors.

The output layer of Model A has one variable, TR, while the input layer includes four neurons—EE, PE, SI, and FL. In Model B, TR and FL are neurons in the input layer, while IU is the output variable. The study used one hidden layer and sigmoid activation on hidden and output layers. Training dataset 70%, testing dataset 30%. Table 10 illustrates the mean and standard deviation of ten neural networks and their Root Mean Square of Error (RMSE). These figures show model prediction accuracy. For the training and testing sets, Model A has an average RMSE standard deviation of 0.1141 and 0.1137. Model B training and testing RMSE mean 0.1076 and 0.1085, respectively. The results indicate accurate forecasting and reliable exogenous-endogenous relationship determination. The independent variable's significance is determined by how effectively different levels predict the result variable's variation, according to Chong (2013). Normalized predictor relevance is relative to maximum importance. The role of independent variables in predicting outcome variables was carefully investigated. Table 11 provides normalized predictor importance. In Table 11, EE predicted trust the most, followed by FL, SI, and PE. FL best predicts IU.

**Table 10:** RMSE for the neural networks

| | **Model A** | | **Model B** | |
|---|---|---|---|---|
| **Network** | **Training** | **Test** | **Training** | **Test** |
| **1** | 0.1152 | 0.1141 | 0.1066 | 0.1107 |
| **2** | 0.1124 | 0.1163 | 0.1077 | 0.1095 |
| **3** | 0.1134 | 0.1109 | 0.1079 | 0.1094 |
| **4** | 0.1150 | 0.1163 | 0.1082 | 0.1078 |
| **5** | 0.1138 | 0.1132 | 0.1067 | 0.1096 |
| **6** | 0.1143 | 0.1136 | 0.1077 | 0.1085 |
| **7** | 0.1171 | 0.1153 | 0.1084 | 0.1060 |

**Table 10:** RMSE for the neural networks (Continued)

| | Model A | | Model B | |
|---|---|---|---|---|
| **Network** | Training | Test | Training | Test |
| **8** | 0.1113 | 0.1147 | 0.1068 | 0.1101 |
| **9** | 0.1126 | 0.1104 | 0.1071 | 0.1087 |
| **10** | 0.1154 | 0.1121 | 0.1091 | 0.1046 |
| **Mean** | 0.1141 | 0.1137 | 0.1076 | 0.1085 |
| **Standard deviation** | 0.0017 | 0.0021 | 0.0008 | 0.0019 |

**Table 11:** Sensitivity analysis

| Model A | | Model B | |
|---|---|---|---|
| **Variable** | **Relative Importance(%)** | **Variable** | **Relative Importance(%)** |
| **EE** | 100.00 | TR | 95.20 |
| **FL** | 90.87 | FL | 100.00 |
| **PE** | 64.27 | | |
| **SI** | 67.66 | | |

## Discussion

Taking into consideration the theories of flow experience and trust, as well as the notions of effort expectancy, performance expectancy, and social influence, this study examined the variables that affect online shopping behaviour on social media platforms. This study's empirical findings have confirmed that social media users' effort expectancy, performance expectancy, and flow experience all favourably impact trust. Furthermore, a statistically significant and positive correlation has been observed between trust and flow experience, as well as between online shopping intention and actual behaviour.

In this study, effort expectancy significantly affects trust, which means that the easy-to-understand and easy-to-use features of social shopping pages persuade social shoppers to trust social shopping. If shoppers can buy the products and services without providing sensitive private information and facing technical difficulties, they will do social shopping, keeping their minds away from trust concerns. This finding is supported by the research works of Fuller et al. (2009), Lankton & McKnight (2011) and Vance et al. (2008). Additionally, our findings empirically prove effort expectancy to impact flow experience. The required low effort and time to learn to use social shopping helps shoppers have more engagement, control, enjoyment, and fun in online shopping on social platforms, ensuring an optimal flow experience for those shoppers. This outcome also corresponds with prior studies (Chang & Wang, 2008; Moon & Kim, 2001; Zhou, 2013). Consistent with previous consumer behaviour research (Loureiro et al., 2018; Zhu et al., 2003), social media users perceived performance expectancy as an essential determinant of trust toward online shopping on social media platforms. This study's participants identified that shopping through social media is useful because this type of shopping allows them to complete shopping tasks more quickly and helps them have better deals than physical shopping or shopping through other e-commerce sites. This shopping type allows the customers to save costs by bringing store shops to customer points instead of forcing customers to move physically to the shops (Ramlugun & Jugurnauth, 2014). Besides, other consumers created reviews and recommendations to increase the usefulness of online shopping on social media platforms. Eventually, these beneficial and convenient features increase users' shopping trust on social media platforms.

In line with previous earlier findings, there is also a positive relationship between social influence and trust (Beyari & Abareshi, 2019; Hu et al., 2019; Yahia et al., 2018). The emotional and informational social supports work as a social influence for trusting online shopping on social media platforms. The referrals through Twitter's 'tweet', Facebook's 'Like', and/or social community discussions from the near and dear trusted ones convince consumers to trust online shopping on social platforms. Sometimes, shoppers on social platforms buy from social pages managed by familiar people as shoppers perceive familiar business owners to be more trustworthy than unfamiliar ones.

The results show that flow experience positively correlates with trust and shopping intention. Social users regularly engage with social media platforms because of curiosity, interest, and fun, which persuade them to increase social media use in frequency and duration. More exploration of social media with a flow experience drives the user to build trust in online shopping on social media platforms. This result is supported by extant studies (Bilgihan, 2016; K.-C. Chang, 2014; Faculty of Economics and Business, Gadjah Mada University, Yogyakarta, Indonesia et al., 2017). When these social users experience a positive flow, they intend to do more online shopping because they feel engaged and curious and enjoy buying products through social media. Previous studies also identified the effect of flow experience on social commerce (Gao & Bai, 2014; Liu et al., 2016; Pelet et al., 2017b; Zhou, 2019). This is in line with some existing online shopping research, and trust is found to be influential for social shopping intention (Chandra et al., 2019; Chen & Barnes, 2007; Hajli, 2015; Lee & Turban, 2001; Singh & Srivastava, 2018). Realizing the usefulness, easiness, and peers' support through reviews, ratings, and recommendations, the user started to trust online shopping on social media. However, in developing countries like Bangladesh, social commerce platforms offer cash-on-delivery (COD) and sometimes check-buy opportunities for buyers, which increase customers' trust in online shopping on social media. Moreover, social media develops trust among social shoppers by providing expediently more comprehensive, up-to-date, and timely information (Logan et al., 2012; Taylor et al., 2011).

In previous research works on online purchasing, a significant causal relationship has been established between social media purchase intent and actual behaviour (Dash & Saji, 2008; Limayem et al., 2000; Singh & Srivastava, 2018). Every time, shopping intention is not transformed into actual shopping behaviour because of changes in shopping arrangements, lack of availability or trialability (Asiedu & Dube, 2020; Carrington et al., 2010; Reza et al., 2012). Thus, the result shows that all these mentioned causes for online shopping on social media distortions are not present in this online shopping research context.

## Implications

**Theoretical Implications**

The present research offers various theoretical insights into the existing body of literature on online shopping, with a particular emphasis on social media-driven online shopping. Firstly, an integrated research model combining UTAUT constructs, flow theory, and trust was proposed and confirmed to provide a comprehensive insight into online shopping behaviour on social media platforms. Many scholars have suggested that combining theories, models, and frameworks increases the explanatory power of the research model evaluating any information systems (DeLone & McLean, 2003; Veeramootoo et al., 2018). Secondly, this proposed model is verified to have robust predictive power as it explained 42.70% of behavioural intention and 41.80% of actual use behaviour. Thus, a similar model can be used in other online shopping arrangements to capture the effect of flow on consumers' behaviour. Thirdly, this paper enriches the flow literature by recognizing technology acceptance constructs (performance expectancy, effort expectancy, social influence) as the flow experienced drivers. This offers a new avenue for other researchers working in consumer psychology and information systems. Finally, this paper has attempted to apply a hybrid methodical approach combining a linear data analysis method (SEM) and an ANN approach to explore deep insights into social media-based online shopping behaviour. Previous researchers supported this combination and argued that the other method's strengths could offset any one method's weaknesses (Scott & Walczak, 2009).

**Practical Implications**

The results of this study have practical implications for professionals seeking to enhance the online shopping experience of consumers through social media platforms. First, the identified factors that work as influencers for social media-based online shopping can be used to develop social commerce pages on social media platforms. Second, the significant position of flow experience in social shopping demands that business persons and developers consider the enjoyment, engagement, and users' interface issues when designing the contents and appearances of social commerce pages. Besides, social media can focus on their platforms to enhance the users' flow experience, fostering social shopping. Last, this research provides an understanding of the formation of the flow experience of social shoppers. For example, social influence from peer groups is positively related to flow experience and online shopping on social media. Thus, managers need to involve social media users and social shoppers to ensure positive reviews, referrals, and ratings of their pages. In addition, users' participation and suggestions in developing aesthetic and interesting views of social commerce pages using pictures, multimedia, quality content, and easy-to-use interfaces will benefit social commerce practitioners.

## Conclusion

The objective of this study is to analyze the purchasing behaviour of clients on social networking platforms. The current study constructed a theoretical framework by including flow theory, the concept of trust, and the three fundamental aspects of the UTAUT model. The researchers evaluated the eight proposed hypotheses using a Structural Equation Modelling (SEM) approach in this work. Subsequently, statistically significant predictors were employed as inputs for a neural model to encompass both linear and nonlinear relationships. Figure 1 illustrates the proposed theory, while Table 6 concisely summarises the main influential variables. The findings indicate that FL is the primary determinant of trust, followed by effort expectancy, social influence, and performance expectancy.

Moreover, compared to trust, the findings suggest that flow experience accounts for a greater variation in the desire to use the construct. According to the Artificial Neural Network model, effort expectancy is the primary predictor of trust, with flow, social influence, and performance expectancy following in order of significance. Regarding the relative significance of predictors for IU, there is consistency between the results of the SEM and ANN models.

*Limitations and Future Research*

This study is subjected to some limitations, which offer opportunities to be addressed in further research. First, this empirical investigation considered cross-sectional data from only one country, Bangladesh. Because of the dynamic nature of human behaviour and the requirement to increase this research outcome's generalizability, future studies can be undertaken by collecting longitudinal data from different countries for time and country-based comparative comparisons. Second, we collected responses using an online self-administered questionnaire, and collected data are self-reported, demanding future qualitative studies based on interviews. Besides, social shopping data traffic can be retrieved and analyzed using deep learning techniques to find deeper insights into social shopping. Third, although this research considered some relevant factors with flow experience, it leaves a gap for future studies to consider several other constructs, such as self-efficacy, personal innovativeness, personal and cultural dimensions, etc. Last, only behavioural intention and use behaviour in the adoption stage were examined in this study. Further research can focus on social shoppers' intention to continue using social media in the post-adoption phase and their willingness to suggest social shopping to others.

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## References

Ajzen, I. (1991). The theory of planned behaviour. *Organizational Behavior and Human Decision Processes*, *50*(2), 179–211. https://doi.org/10.1016/0749-5978(91)90020-T

Al-Saedi, K., Al-Emran, M., Ramayah, T., & Abusham, E. (2020). Developing a general extended UTAUT model for M-payment adoption. Technology in Society, 62, 101293. https://doi.org/ 10.1016/j.techsoc.2020.101293

Arceo, P. B. M., Cumahig, I. R. C., Michael, B., & Buenaventura, M. J. V. (2018). The impact of social media platforms on online consumers' intention to purchase in the restaurant industry. *Global Journal of Emerging Trends in E-Business, Marketing and Consumer Psychology*, *4*(1), 2311–3170.

Asiedu, R., & Dube, F. N. M. (2020). Antecedents of Chinese consumer online shopping behaviour. *Asian Journal of Business Research*, *10*(2), 91–110.

Auger, P., & Devinney, T. M. (2007). Do What Consumers Say Matter? The Misalignment of Preferences with Unconstrained Ethical Intentions. *Journal of Business Ethics*, *76*(4), 361–383. https://doi.org/10.1007/s10551-006-9287-y

Belanche, D., Casaló, L. V., & Flavián, C. (2012). Integrating trust and personal values into the Technology Acceptance Model: The case of e-government services adoption. *Cuadernos de Economía y Dirección de La Empresa*, *15*(4), 192–204. https://doi.org/10.1016/j.cede.2012.04.004

Bernoff, J., & Li, C. (n.d.). Effects of Brand Attitude and Familiarity. *The Journal of Marketing*, *59*(1), 63–77.

Beyari, H., & Guth, A. (2018). Customer Experience in Social Commerce Websites: Toward an Integrated Conceptual Framework. *Journal of Management Research*, 10(3), 52. https://doi.org/10.5296/jmr.v10i3.13185

Beyari, H., & Abareshi, A. (2019). *The interaction of trust and social influence factors in the social commerce environment*. 931–944.

Bilgihan, A. (2016). Gen Y customer loyalty in online shopping: An integrated model of trust, user experience and branding. *Computers in Human Behavior*, pp. *61*, 103–113. https://doi.org/10.1016/j.chb.2016.03.014

Bligh, M. C. (2017). Leadership and Trust. In J. Marques & S. Dhiman (Eds.), *Leadership Today* (pp. 21–42). Springer International Publishing. https://doi.org/10.1007/978-3-319-31036-7_2

Carlson, J., Rahman, M., Voola, R., & De Vries, N. (2018). Customer engagement behaviours in social media: Capturing innovation opportunities. *Journal of Services Marketing*, *32*(1), 83–94.

Carrington, M. J., Neville, B. A., & Whitwell, G. J. (2010). Why ethical consumers don't walk their talk: Towards a framework for understanding the gap between the ethical purchase intentions and actual buying behaviour of ethically minded consumers. *Journal of Business Ethics*, *pp. 97*, 139–158.

Celik, H. (2016). Customer online shopping anxiety within the Unified Theory of Acceptance and Use Technology (UTAUT) framework. *Asia Pacific Journal of Marketing and Logistics*, *28*(2). https://doi.org/10.1108/APJML-05-2015-0077

Chan, F. T. S., & Chong, A. Y. L. (2012). An SEM–neural network approach for understanding determinants of inter-organizational system standard adoption and performances. *Decision Support Systems*, *54*(1), 621–630. https://doi.org /10.1016/ j. dss.2012.08.009

Chandra, E., Liu, S., Sfenrianto, S., & Wang, G. (2019). Analysis of the Effect of Security and Trust on Buying Decisions on the Tokopedia Mobile Apps. *2019 4th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE)*, 452–456. https://doi.org/10.1109/I CIT ISEE 484 80. 201 9.9003846

Chandra, S., Srivastava, S. C., & Theng, Y.-L. (2010). Evaluating the Role of Trust in Consumer Adoption of Mobile Payment Systems: An Empirical Analysis. *Communications of the Association for Information Systems*, *27*. https://doi.org/1 0.17 705/1CAIS.02729

Chang, H. H., & Wang, I. C. (2008). An investigation of user communication behaviour in computer-mediated environments. *Computers in Human Behavior*, *24*(5), 2336–2356.

Chang, K.-C. (2014). Examining the Effect of Tour Guide Performance, Tourist Trust, Tourist Satisfaction, and Flow Experience on Tourists' Shopping Behavior. *Asia Pacific Journal of Tourism Research*, *19*(2), 219–247. https://doi.org /10.108 0/1094 1665.2012.739189

Chang, S. E., Liu, A. Y., & Shen, W. C. (2017). User trust in social networking services: A comparison of Facebook and LinkedIn. *Computers in Human Behavior*, pp. *69*, 207–217. https://doi.org/10.1016/j.chb.2016.12.013

Chang, Y. P., & Zhu, D. H. (2012). The role of perceived social capital and flow experience in building users' continuance intention to social networking sites in China. *Computers in Human Behavior*, *28*(3), 995–1001.https://doi.org/10.1016/j.chb.201 2.01.001

Chen, L. (2014). The influence of social media on consumer behaviour: An empirical study on factors influencing consumer purchase intention in China under the social media context. *Denmark: Aarhus University*.

Chen, Y., & Barnes, S. (2007). Initial trust and online buyer behaviour. *Industrial Management & Data Systems*, *107*(1), 21–36.

Chong, A. Y.-L. (2013). A two-staged SEM-neural network approach for understanding and predicting the determinants of m-commerce adoption. *Expert Systems with Applications*, *40*(4), 1240–1247. https://doi.org/10.1016/j.eswa.2012.08.067

Chung, C., & Austria, K. P. (2012). Attitudes toward product messages on social media: Examining online shopping perspectives among young consumers. *International Journal of E-Services and Mobile Applications (IJESMA)*, *4*(4), 1–14.

Cohen, J. (2013). *Statistical Power Analysis for the Behavioral Sciences* (0 ed.). Routledge. https://doi.org/10.4324/9780203771587

Compeau, D. R., & Higgins, C. A. (1995). Computer Self-Efficacy: Development of a Measure and Initial Test. *MIS Quarterly*, *19*(2), 189. https://doi.org/10.2307/249688

Csikszentmihalyi, M. (1990). *Flow. The Psychology of Optimal Experience. New York (HarperPerennial) 1990.*

Csíkszentmihályi, M., & Csikszentmihalyi, I. S. (1992). *Optimal experience: Psychological studies of flow in consciousness*. Cambridge University Press.

Dash, S., & Saji, K. (2008). The role of consumer self-efficacy and website social-presence in customers' adoption of B2C online shopping: An empirical study in the Indian context. *Journal of International Consumer Marketing*, *20*(2), 33–48.

Davis, F. D. (1989). Perceived Usefulness, Ease of Use, and User Acceptance of Information Technology. *MIS Quarterly*, *13*(3), 319. https://doi.org/10.2307/249008

DeLone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, *19*(4), 9–30.

Edwards, S. M. (2011). A Social Media Mindset. *Journal of Interactive Advertising*, *12*(1), 1–3. https://doi.org/10.1080/15252019.2011.10722186

Fishbein, M., & Ajzen, I. (1975). *Belief, attitude, intention, and behaviour: An introduction to theory and research*. Addison-Wesley Pub. Co.

Fogel, J., & Zachariah, S. (2017). Intentions to use the Yelp review website and purchase behaviour after reading reviews. *Journal of Theoretical and Applied Electronic Commerce Research*, *12*(1), 53–67.

Foxall, G. R. (2015). *The Routledge companion to consumer behaviour analysis*. Routledge.

Fuller, M. A., Serva, M. A., & Baroudi, J. (2009). Clarifying the integration of trust and TAM in e-commerce environments: Implications for systems design and management. *IEEE Transactions on Engineering Management*, *57*(3), 380–393.

Gao, L., & Bai, X. (2014). Online consumer behaviour and its relationship to website atmospheric induced flow: Insights into online travel agencies in China. *Journal of Retailing and Consumer Services*, *21*(4), 653–665.

Gefen & Straub. (2003). Managing User Trust in B2C e-Services. *E-Service Journal*, *2*(2), 7. https://doi.org/10.2979/esj.2003.2.2.7

Geisser, S. (1974). A predictive approach to the random effect model. *Biometrika*, *61*(1), 101–107. https://doi.org/10.1093/biomet/61.1.101

Gibreel, O., AlOtaibi, D. A., & Altmann, J. (2018). Social commerce development in emerging markets. *Electronic Commerce Research and Applications*, *27*, 152–162.

Goodhue, D. L., & Thompson, R. L. (1995). Task-Technology Fit and Individual Performance. *MIS Quarterly*, *19*(2), 213. https://doi.org/10.2307/249689

Guo, Y. M., & Poole, M. S. (2009). Antecedents of flow in online shopping: A test of alternative models. *Information Systems Journal*, *19*(4), 369–390.

Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, *31*(1), 2–24. https://doi.org/10.1108/EBR-11-2018-0203

Hajli, N. (2015). Social commerce constructs and consumer's intention to buy. *International Journal of Information Management*, *35*(2), 183–191.

Heinrichs, J. H., Lim, J., & Lim, K. (2011). Influence of social networking site and user access method on social media evaluation. *Journal of Consumer Behaviour*, *10*(6), 347–355.

Henseler, J., Hubona, G., & Ray, P. A. (2016). Using PLS path modeling in new technology research: Updated guidelines. *Industrial Management and Data Systems*, 116(1), 2-20.

Hew, T.-S., Leong, L.-Y., Ooi, K.-B., & Chong, A. Y.-L. (2016). Predicting Drivers of Mobile Entertainment Adoption: A Two-Stage SEM-Artificial-Neural-Network Analysis. *Journal of Computer Information Systems*, *56*(4), 352–370. https://doi.org/10.1080/08874417.2016.1164497

Hoffman, D. L., & Novak, T. P. (1996). Marketing in Hypermedia Computer-Mediated Environments: Conceptual Foundations. *Journal of Marketing*, *60*(3), 50–68. https://doi.org/10.1177/002224299606000304

Hoque, R., & Sorwar, G. (2017). Understanding factors influencing the adoption of mHealth by the elderly: An extension of the UTAUT model. International Journal of Medical Informatics, 101, 75–84. https://doi.org/10.1016/j.i jmedinf.2017.02.002

Hsu, C.-L., Chang, K.-C., Kuo, N.-T., & Cheng, Y.-S. (2017). The mediating effect of flow experience on social shopping behaviour. *Information Development*, *33*(3), 243–256. https://doi.org/10.1177/0266666916651918

Hu, X., Chen, X., & Davison, R. M. (2019). Social support, source credibility, social influence, and impulsive purchase behaviour in social commerce. *International Journal of Electronic Commerce*, *23*(3), 297–327.

Hu, X., Huang, Q., Zhong, X., Davison, R. M., & Zhao, D. (2016). The influence of a social shopping website's peer characteristics and technical features on a consumer's purchase intention. *International Journal of Information Management*, *36*(6), 1218–1230.

Huang, Z., & Benyoucef, M. (2013). From e-commerce to social commerce: A close look at design features. *Electronic Commerce Research and Applications*, *12*(4), 246–259.

Huang, Z., & Benyoucef, M. (2017). The effects of social commerce design on consumer purchase decision-making: An empirical study. *Electronic Commerce Research and Applications*, pp. *25*, 40–58.

Hussain, S., Li, Y., & Li, W. (2021). Influence of platform characteristics on purchase intention in social commerce: Mechanism of psychological contracts. *Journal of Theoretical and Applied Electronic Commerce Research*, *16*(1), 1–17.

International Burch University, Poturak, M., Softić, S., & International Burch University. (2019). Influence of Social Media Content on Consumer Purchase Intention: Mediation Effect of Brand Equity. *Eurasian Journal of Business and Economics*, *12*(23), 17–43. https://doi.org/10.17015/ejbe.2019.023.02

Jarvenpaa, S. L., Tractinsky, N., & Saarinen, L. (2006). Consumer Trust in an Internet Store: A Cross-Cultural Validation. *Journal of Computer-Mediated Communication*, *5*(2), 0–0. https://doi.org/10.1111/j.1083-6101.1999.tb00337.x

Kamboj, S., Sarmah, B., Gupta, S., & Dwivedi, Y. (2018). Examining branding co-creation in brand communities on social media: Applying the paradigm of Stimulus-Organism-Response. *International Journal of Information Management*, pp. *39*, 169–185.

Kao, T.-Y., Yang, M.-H., Wu, J.-T. B., & Cheng, Y.-Y. (2016). Co-creating value with consumers through social media. *Journal of Services Marketing*, *30*(2), 141–151.

Kaplan, A. M., & Haenlein, M. (2010). Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons*, *53*(1), 59–68.

Khasawneh, M. H. A., Hujran, O., & Abdrabbo, T. (2018). A quantitative examination of the factors influencing users' perceptions of trust towards mobile banking services. *International Journal of Internet Marketing and Advertising*, *12*(2), 181. https://doi.org/10.1504/IJIMA.2018.090957

Kim, N., & Kim, W. (2018). Do your social media lead you to make social deal purchases? Consumer-generated social referrals for sales via social commerce. *International Journal of Information Management*, *39*, 38–48.

Kline RB (2015). *Principles and practice of structural equation modeling*. New York: Guilford publications.

Kline, R. B. (2023). *Principles and practice of structural equation modeling* (Fifth edition). The Guilford Press.

Korzaan, M. L. (2003). Going with the flow: Predicting online purchase intentions. *Journal of Computer Information Systems*, *43*(4), 25–31.

Koufaris, M. (2002). Applying the technology acceptance model and flow theory to online consumer behaviour. *Information Systems Research*, *13*(2), 205–223.

Lankton, N. K., & McKnight, D. H. (2011). What does it mean to trust Facebook?: Examining technology and interpersonal trust beliefs. *ACM SIGMIS Database: The DATABASE for Advances in Information Systems*, *42*(2), 32–54. https://doi.org/10.1145/1989098.1989101

Lee, M. K., & Turban, E. (2001). A trust model for consumer Internet shopping. *International Journal of Electronic Commerce*, *6*(1), 75–91.

Lee, M.-C., & Tsai, T.-R. (2010). What Drives People to Continue to Play Online Games? An Extension of Technology Model and Theory of Planned Behavior. *International Journal of Human-Computer Interaction*, *26*(6), 601–620. https://doi.org/ 10.108 0/1 0447311003781318

Leong, L.-Y., Hew, T.-S., Ooi, K.-B., Lee, V.-H., & Hew, J.-J. (2019). A hybrid SEM-neural network analysis of social media addiction. *Expert Systems with Applications*, *133*, 296–316. https://doi.org/10.1016/j.eswa.2019.05.024

Li, X., Hess, T. J., & Valacich, J. S. (2008). Why do we trust new technology? A study of initial trust formation with organizational information systems. *The Journal of Strategic Information Systems*, *17*(1), 39–71. https://doi.org/10.1016/j.jsis.2008.01.0 01

Liebana-Cabanillas, F., & Alonso-Dos-Santos, M. (2017). Factors determining the adoption of Facebook commerce: The moderating effect of age. *Journal of Engineering and Technology Management*, *44*, 1–18.

Limayem, M., Khalifa, M., & Frini, A. (2000). What makes consumers buy from the Internet? A longitudinal study of online shopping. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, *30*(4), 421–432.

Liu, H., Chu, H., Huang, Q., & Chen, X. (2016). Enhancing the flow experience of consumers in China through interpersonal interaction in social commerce. *Computers in Human Behavior*, *58*, 306–314.

Logan, K., Bright, L. F., & Gangadharbatla, H. (2012). Facebook versus television: Advertising value perceptions among females. *Journal of Research in Interactive Marketing*, *6*(3), 164–179.

Loureiro, S. M. C., Cavallero, L., & Miranda, F. J. (2018). Fashion brands on retail websites: Customer performance expectancy and e-word-of-mouth. *Journal of Retailing and Consumer Services*, *41*, 131–141. https://doi.org/10.1016/j.jretconser.2017.12.005

Lu, Y., Yang, S., Chau, P. Y. K., & Cao, Y. (2011). Dynamics between the trust transfer process and intention to use mobile payment services: A cross-environment perspective. *Information & Management*, *48*(8), 393–403. https://doi.org/10.1016/ j.im.2011.09.006

Mahnke, R., Benlian, A., & Hess, T. (2015). A grounded theory of online shopping flow. *International Journal of Electronic Commerce*, *19*(3), 54–89.

Mangold, W. G., & Faulds, D. J. (2009). Social media: The new hybrid element of the promotion mix. *Business Horizons*, *52*(4), 357–365.

Martilla, J. A., & James, J. C. (1977). Importance-Performance Analysis. *Journal of Marketing*, *41*(1), 77–79. https://doi.org/10.1177/002224297704100112

Mensah, I. K. (2019). Predictors of Electronic Government Services Adoption: The African Students’ Perspective in China. *International Journal of Public Administration*, *42*(12), 997–1009. https://doi.org/10.1080/01900692.2019.1572621

Mir, I., & Zaheer, A. (2012). Verification of social impact theory claims in a social media context. *Journal of Internet Banking and Commerce*, *17*(1), 1.

Moon, J.-W., & Kim, Y.-G. (2001). Extending the TAM for a World-Wide-Web context. *Information & Management*, *38*(4), 217–230. https://doi.org/10.1016/S0378-7206(00)00061-6

Nadeem, W., Andreini, D., Salo, J., & Laukkanen, T. (2015). Engaging consumers online through websites and social media: A gender study of Italian Generation Y clothing consumers. *International Journal of Information Management*, *35*(4), 432–442.

Nel, J., & Boshoff, C. (2017). Development of application-based mobile-service trust and online trust transfer: an elaboration likelihood model perspective. Behaviour & Information Technology, 36(8), 809–826.https://doi.org /1 0.1080/0 144 929 x.2017. 1296493

O'Brien, R. M. (2007). A Caution Regarding Rules of Thumb for Variance Inflation Factors. *Quality & Quantity*, *41*(5), 673–690. https://doi.org/10.1007/s11135-006-9018-6

Pelet, J.-É., Ettis, S., & Cowart, K. (2017a). Optimal experience of flow enhanced by telepresence: Evidence from social media use. *Information & Management*, *54*(1), 115–128.

Pelet, J.-É., Ettis, S., & Cowart, K. (2017b). Optimal experience of flow enhanced by telepresence: Evidence from social media use. *Information & Management*, *54*(1), 115–128.

Permatasari, A., & Kartikowati, M. (2018). The influence of website design on customer online trust and perceived risk towards purchase intention: A case of O2O commerce in Indonesia. *International Journal of Business and Globalisation*, *21*(1), 74–86.

Permatasari, A., & Kuswadi, E. (2017). The impact of social media on consumers' purchase intention: A study of e-commerce sites in Jakarta, Indonesia. *Review of Integrative Business and Economics Research*, *6*, 321.

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioural research: A critical literature review and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Ramlugun, V. G., & Jugurnauth, L. (2014). The scope of social media browsing and online shopping for Mauritian e-retailers: A study based on utilitarian and hedonic values. *Review of Integrative Business and Economics Research*, *3*(2), 219–241.

Rahi, S., Othman Mansour, M. M., Alghizzawi, M., & Alnaser, F. M. (2019). Integration of UTAUT model in Internet banking adoption context. Journal of Research in Interactive Marketing, 13(3), 411–435. https://doi.org/ 10.11 08/ jrim-02-2018-0032

Rathore, A. K., Ilavarasan, P. V., & Dwivedi, Y. K. (2016). Social media content and product co-creation: An emerging paradigm. *Journal of Enterprise Information Management*, *29*(1), 7–18.

Reza Jalilvand, M., & Samiei, N. (2012). The effect of electronic word of mouth on brand image and purchase intention: An empirical study in the automobile industry in Iran. *Marketing Intelligence & Planning*, *30*(4), 460–476.

Scott, J. E., & Walczak, S. (2009). Cognitive engagement with a multimedia ERP training tool: Assessing computer self-efficacy and technology acceptance. *Information & Management*, *46*(4), 221–232.

Sharifi fard, S., Tamam, E., Hj Hassan, M. S., Waheed, M., & Zaremohzzabieh, Z. (2016). Factors affecting Malaysian university students’ purchase intention in social networking sites. *Cogent Business & Management*, *3*(1), 1182612.

Sheppard, B. H., Hartwick, J., & Warshaw, P. R. (1988). The Theory of Reasoned Action: A Meta-analysis of Past Research with Recommendations for Modifications and Future Research. *Journal of Consumer Research*, *15*(3), 325. https://doi.org/10.1086/209170

Shin, D.-H. (2010). Modeling the Interaction of Users and Mobile Payment System: Conceptual Framework. *International Journal of Human-Computer Interaction*, *26*(10), 917–940. https://doi.org/10.1080/10447318.2010.502098

Sim, J.-J., Tan, G. W.-H., Wong, J. C. J., Ooi, K.-B., & Hew, T.-S. (2014). Understanding and predicting the motivators of mobile music acceptance – A multi-stage MRA-artificial neural network approach. *Telematics and Informatics*, *31*(4), 569–584. https://doi.org/10.1016/j.tele.2013.11.005

Singh, S., & Srivastava, S. (2018). The moderating effect of product type on online shopping behaviour and purchase intention: An Indian perspective. *Cogent Arts & Humanities*, *5*(1), 1495043.

Streukens, S., Leroi-Werelds, S., & Willems, K. (2017). Dealing with Nonlinearity in Importance-Performance Map Analysis (IPMA): An Integrative Framework in a PLS-SEM Context. In H. Latan & R. Noonan (Eds.), *Partial Least Squares Path Modeling* (pp. 367–403). Springer International Publishing. https://doi.org/10.1007/978-3-319-64069-3_17

Swani, K., Milne, G. R., Brown, B. P., Assaf, A. G., & Donthu, N. (2017). What messages to post? Evaluating the popularity of social media communications in business versus consumer markets. *Industrial Marketing Management*, *pp. 62*, 77–87.

Tan, G. W.-H., Ooi, K.-B., Leong, L.-Y., & Lin, B. (2014). Predicting the drivers of behavioural intention to use mobile learning: A hybrid SEM-Neural Networks approach. *Computers in Human Behavior*, pp. *36*, 198–213. https://doi.org/10.1016/j.chb.2014.03.052

Taylor, D. G., Lewin, J. E., & Strutton, D. (2011). Friends, fans, and followers: Do ads work on social networks?: How gender and age shape receptivity. *Journal of Advertising Research*, *51*(1), 258–275.

Tsoukalas, L. H., & Uhrig, R. E. (1997). *Fuzzy and neural approaches in engineering*. Wiley.

Vance, A., Elie-Dit-Cosaque, C., & Straub, D. W. (2008). Examining trust in information technology artefacts: The effects of system quality and culture. *Journal of Management Information Systems*, *24*(4), 73–100.

Veeramootoo, N., Nunkoo, R., & Dwivedi, Y. K. (2018). What determines the success of an e-government service? Validation of an integrative model of e-filing continuance usage. *Government Information Quarterly*, *35*(2), 161–174.

Venkatesh, M., Davis, & Davis. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Venkatesh, V., & Davis, F. D. (2000). A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. *Management Science*, *46*(2), 186–204. https://doi.org/10.1287/mnsc.46.2.186.11926

Wang, H., & Hu, Z. (2009). Research on online consumer behaviour based on experience. *2009 16th International Conference on Industrial Engineering and Engineering Management*, 364–368. https://doi.org/10.1109/ICIEEM.2009.5344572

Wei, Y., Wang, C., Zhu, S., Xue, H., & Chen, F. (2018). Online purchase intention of fruits: Antecedents in an integrated model based on technology acceptance model and perceived risk theory. *Frontiers in Psychology*, *9*, 1521.

Wu, L., Chiu, M.-L., & Chen, K.-W. (2020). Defining the determinants of online impulse buying through a shopping process of integrating perceived risk, expectation-confirmation model, and flow theory issues. *International Journal of Information Management*, *52*, 102099.

Yahia, I. B., Al-Neama, N., & Kerbache, L. (2018). Investigating the drivers for social commerce in social media platforms: Importance of trust, social support and the platform perceived usage. *Journal of Retailing and Consumer Services*, *41*, 11–19.

Zhang, H., Lu, Y., Gupta, S., & Zhao, L. (2014). What motivates customers to participate in social commerce? The impact of technological environments and virtual customer experiences. *Information & Management*, *51*(8), 1017–1030.

Zhang, T., Tao, D., Qu, X., Zhang, X., Zeng, J., Zhu, H., & Zhu, H. (2020). Automated vehicle acceptance in China: Social influence and initial trust are key determinants. *Transportation Research Part C: Emerging Technologies*, *112*, 220–233. https://doi.org/10.1016/j.trc.2020.01.027

Zhou, T. (2012). Examining location-based services usage from the perspectives of a unified theory of acceptance and use of technology and privacy risk. *Journal of Electronic Commerce Research*, *13*(2), 135.

Zhou, T. (2013). The effect of flow experience on user adoption of mobile TV. *Behaviour & Information Technology*, *32*(3), 263–272.

Zhou, T. (2014). An Empirical Examination of Initial Trust in Mobile Payment. *Wireless Personal Communications*, *77*(2), 1519–1531. https://doi.org/10.1007/s11277-013-1596-8

Zhou, T. (2019). The effect of flow experience on users' social commerce intention. *Kybernetes*, *49*(10), 2349–2363. https://doi.org/10.1108/K-03-2019-0198

Zhu, W., Nah, F. F.-H., & Zhao, F. (2003). Factors influencing users' adoption of mobile computing. In *Managing e-commerce and mobile computing technologies* (pp. 260–271). IGI Global.