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Editorial
Special Issue Editors' Introduction: Impact of Social Media on Businesses

In today's electronic age, companies are almost required to use social media to interact and engage with customers. The methods and means to reach customers vary, as the identification of what can be considered "social media" continues to evolve with new innovations. This continual evolution and innovation of social media platforms makes it difficult to clearly define what social media is; however, the difficulty in defining it does not minimize the effects and consequences social media has on businesses.

To classify and unify the fragmented uses of social media among academics and practitioners, El Ouirdi *et al.* (2014) defined social media broadly as a set of mobile and web-based platforms built on Web 2.0 technologies, that have the intent of reaching and involving large audiences, by allowing users at all levels (micro-, meso- and macro-) to i) share and geo-tag user-generated content; ii) collaborate; and iii) build networks and communities. Such interaction and engagement help in generating customer trust in the company (Sashi, 2012). Consumers' trust in others who appear similar to themselves is one of the main factors that make social media marketing powerful. Hence, marketers desire to tap into that trust through the power of earned media and by engaging in conversation with consumers.

This special issue seeks to deepen our understanding of social media from new perspectives and to consider emerging issues that companies face in this competitive age. We begin by considering the acceptance of technological innovations and emerging social media platforms. The continual evolution of social media technologies, and the products that interface these social media platforms, must be considered as businesses seek to determine which aspects of social media should be included in their marketing strategy. Firms review the technology acceptance levels of customers, and segment customers based on labels such as early adopters through laggards. Therefore, it seems only logical that the innovation acceptance level of consumers for emerging social media platforms should be considered as well. Thus, Dena Hale (Southeast Missouri State University), Sarfraz Khan (University of Louisiana Lafayette), Ravindra Thakur (The PNG University of Technology) and Arifin Angriawan (Purdue University Northwest) discuss the topic of gifted innovation. Gifted innovations are those innovations that are new in the market place. The authors propose a model which incorporates important factors that enhance customers' intention to adopt technology. Results indicate that attitude and technology apprehension are predictors of technology adoption intention. Surprisingly, innovators, while behaviorally did adopt high technology, were not found to have the intention to adopt it. This may transfer to the use and adoption of new social media platforms and businesses' ability to measure true behavior.

In line with the concept of user-generated content, Dhoha AlSaleh (Gulf University for Science and Technology) examines the influence expert bloggers have on consumer decision making and purchase. Based within the context of Kuwaiti consumers, it is found that consumers are influenced more by blogger-created content when the blogger is trusted and perceived as an expert. The impact on businesses is important; their strategy and promotion should include, and be aligned with, external bloggers and stakeholders who are deemed influential on consumer target groups.

Peng Xie (California State University, East Bay), Jiming Wu (California State University, East Bay) and Chongqi Wu (California State University, East Bay) continue the examination of new technologies and social media platforms. Xie and colleagues showcase the predictive power of social data across information channels from the Bitcoin market. Bitcoin is a new type of currency, specifically a peer-to-peer electronic cash system known as digital currency. By comparing the predictive power across different information channels and different user groups, the authors found that i) while speculative information predicts both long-term and short-term returns effectively, fundamental-related information only predicts long-term returns, and ii) prediction accuracy is higher for less active users than for active users on social media, especially in long-term prediction.

In the final paper of this special issue, Liam Brunt (Norwegian School of Economics) and Erik Meidell (Norwegian School of Economics) review aspects of crowdsourced data that affect the data's accuracy, truthfulness and true representation. The authors track the origins of crowdsourcing back to the 1850s with the creation of the trade directories in Britain during the Industrial Revolution. The findings are applied to modern day trade/business directories, such as Yelp, suggesting the principles of this social media principle are not new. While current day crowdsourced data may be more difficult to evaluate, the authors provide aspects of the crowdsourcing that may affect the level of truthfulness, accuracy and representation.

In conclusion, the papers reveal that social media is diverse and emergent. Accepted theories in disciplines, such as Marketing, Economics, and Management, may hold true with respect to social media; however, this may vary by the specific social media platform considered. The impact social media has on businesses may be as diverse and emergent as the social media platforms themselves. Finally, the special issue editors would like to thank the special issue reviewers, Dhoha AlSaleh (Gulf University for Science and Technology), Foster Roberts (Southeast Missouri State University), Linda Mullen (Georgia Southern University), Sarfraz Khan (University of Louisiana at Layfayette) and Sandipan Sen (Southeast Missouri State University), for their time and insightful feedback.

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Gifted Innovation: An Examination Using Different Business Theories

By DENA HALE, SARFRAZ KHAN, RAVINDRA THAKUR, AND ARIFIN ANGRIAWAN*

Drawing on insights from an extensive business literature review such as marketing, management, and accounting, a model which incorporates important factors that enhance customers' intention to adopt technology is proposed. The factors examined in this study include customers' attitude toward technology, innovativeness, technology familiarity/knowledge, and technology apprehension. Results indicated that attitude and technology apprehension are predictors of technology adoption intention. Surprisingly, innovators, while behaviorally did adopt high technology, were not found to have the intention to adopt it. The article concludes with managerial implications, limitations, and future research.

Keywords: Gifted Innovation, Technology Adoption, Adoption Intention

JEL Classification: O14

I. Introduction

The emergence of high-technology, such as the PDA, iPod, TReO and cell phones, is proclaimed as gifted innovation. Such innovation has enhanced the eagerness of both scholars and practitioners to understand the factors that drive consumers to adopt high-tech products. The area of high-technology commands considerable importance and has received much attention from scholars. However, the rapid development of new technology brings about an increased need for continued examination of changes in consumer behavior. Drawing on insights from an extensive literature review of high-technology theories, such as technology adoption model (TAM) (Davis, 1989), diffusion of innovation theory (DIT) (Rogers, 1983 and 1995), and theory of planned behavior (TPB) (Azjen, 1985 and 1991), a model is proposed. The proposed model incorporates important factors which enhance customers' intention to adopt technology. The factors examined in this study include customers' attitude toward technology, innovativeness, technology familiarity/knowledge, and technology apprehension. The consequence of *intention* is actual *adoption* of technological products.

Most researchers would not disagree that the factors presented here are related to technology adoption intention; however, to the best of our knowledge there is a lack of scholarly

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work empirically showing all these predictors within a single framework. The objective of this study is to fill that void in the literature and ascertain the predictors of technology adoption intention. In addition, our model attempts to explain whether or not technology adoption intention actually leads to technology adoption. Building on the proposed model, research hypotheses are developed and tested.

II. Literature Review

A. Theory of Planned Behavior

The *theory of planned behavior* (TPB) (Azjen, 1988 and 1991) extended the theory of reasoned action (TRA) (Fishbein and Azjen, 1975) by adding another individual determinant of intention on behavior: perceived behavioral control to the attitude and subjective norm constructs. Both theories (e.g., TPB and TRA) are used to explain an individual's behavior (Oh *et al.*, 2003). The TPB theory posits that an individual's attitude toward the behavior, subjective norms and perceived behavioral control lead to intention toward the behavior. It is this intention that leads to actual behavioral actions. TPB has been used in past research to explain and understand an individual's acceptance of new technologies (e.g. Oh *et al.*, 2003; Venkatesh *et al.*, 2000; Mathieson, 1991). A more recent study by Hsu *et al*. (2006) used the theory of planned behavior to examine the individual's intention to continue purchasing (continuance intention) in an online environment. In their cross-cultural study of online social interactions, Bagozzi *et al*. (2006) found that attitudes and perceived behavioral control significantly led to intentions, which led to behavior as posited by the TPB. However, contrary to the theory, subjective norms did not significantly affect intention.

In this study, we focus on the factors which influence the consumer's willingness/ intention to adopt new technologies. According to TPB (Azjen, 1988 and 1991), strong customer attitude toward a product and/or a service influences his/her intention to adopt it. Morris and Venkatesh's (2000) study on technology adoption intention in the work force indicated that "compared to older workers, younger workers' technology usage decisions were more strongly influenced by attitude toward using the technology" (p. 375). Our study extends TPB by incorporating other individual factors, besides attitude, that enhance customer willingness to adopt technology, which in turn influences actual technology adoption.

B. Technology Acceptance Model

According to the *technology acceptance model* (TAM) (Davis, 1989), two important factors that drive a customer's intention/willingness to adopt a new technological gadget are *perceived ease of use* and *perceived usefulness.* According to Davis (1989), perceived ease of use and perceived usefulness of the technology are the antecedents for technology adoption. However, in a study on lecturer adoption of internet teaching aids, Darsono (2005) found that perceived usefulness and perceived ease of use were significant predictors of *attitude* toward using the internet aid but <u>not</u> of the actual *intention* to use it, which should lead to adoption. In the present study, if a customer is familiar with and knowledgeable of an innovative product, it is assumed that s/he will find the technology to be more useful and easier to use, thereby reducing her/his fear and uncertainty in using the technology. The result of the decreased uncertainty and fear is the enhancement of intention to adopt the technology, leading to actually adoption behavior.

C. Diffusion of Innovation Theory

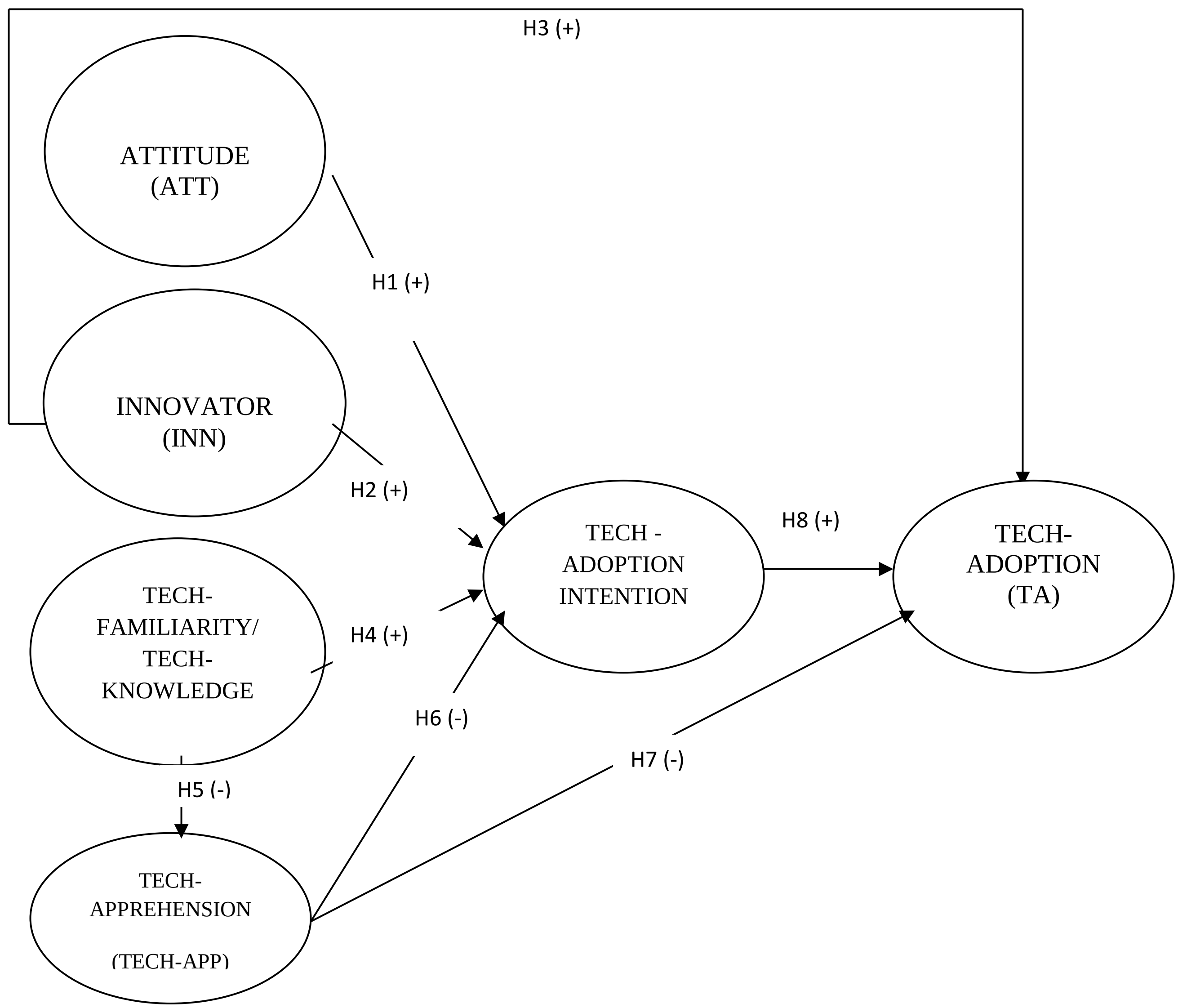
Diffusion of innovation theory (DIT) (Rogers, 1995; Zaltman *et al.*, 1973) also plays an important role in increasing customer adoption intention and actual adoption of a product. It has its root from sociology (Venkatesh *et al*., 2003). The theory of diffusion "has been used since the 1960s to study a variety of innovations ranging from agricultural tools to organizational innovations" (Venkatesh *et al*, 2003, p. 431). Zaltman *et al.* (1973) posited that customers will consider a product to be innovative if the product is perceived as new and relevant. If they consider the product to be new and relevant then innovators should be willing to experiment with the new technology either by purchase or by seeking additional information about the new technological products present in the market.

Recently, studies examining DIT have done so by combining the theory with the TAM and TPB theories in hopes of developing a more unified view of technology information acceptance (see Venkatesh *et al.*, 2003; Yi *et al.*, 2006). In the current study, elements of each theoretical framework are incorporated and extended to other factors that may influence customers' willingness to adopt and/or their actual adoption of new technology. The next section deals with the research framework and hypotheses development.

III. A Framework for Understanding Technology Adoption

The technology adoption framework (Figure 1) derived in this study is based on extensive review of marketing literature as well as the above three theories taken from social psychology and management. The present framework tries to explain the following research questions: (1) Are the customer's attitude (ATT), innovativeness (INN), technology familiarity/knowledge (TECH-KNOW), and technology apprehension (TECH-APP) predictors of technology adoption intention (TAI); (2) Is there a direct relationship between innovativeness (INN) and technology adoption (TA); (3) Does technology familiarity/knowledge (TECH-KNOW) result in a decrease in customer's apprehension in using technology; (4) Is technology apprehension (TECH-APP) the antecedent of technology adoption (TA) or is the relationship between the two mediated by technology adoption intention (TAI); (5) Is technology adoption intention (TAI) the predictor of actual adoption of technology (TA).

Figure 1: Proposed Model



A. Attitude to Technology Adoption Intention

Two theories in social psychology literature, the theory of reasoned action (Fishbein and Azjen, 1975) and the theory of planned behavior (Azjen, 1985) have suggested that customer's positive belief helps in generating positive customer attitude. In turn, attitude drives customer intention (e.g., Fishbein and Azjen, 1975; Hillhouse *et al.*, 1997), which leads to the occurrence of the final behavior (Azjen, 1985 and 1991). According to Oh *et al.* (2003), both TPB and TAM have indicated the importance of customers' attitude toward the technology as an important determinant in explaining behavioral intention. Similarly, in the context of technology adoption, it can be said that if customers find a new technology gadget to be useful, they will have a positive attitude toward that technology and will be more likely to have greater willingness to try it. If satisfied, the consumer is more likely to adopt technology.

An empirical study by Curran *et al.* (2003), in the context of self-service technology (SST), found that a consumer's positive attitude toward a service provider and its technologies influenced customer's intention to use the SSTs. Wu (2006) further demonstrated the existence of a positive relationship between attitude and purchase intention. This leads to the following hypothesis:

H1*: Customer attitude toward the technology is positively related to customer intention to adopt new technology.*

B. Innovator to Technology Adoption Intention and Technology Adoption

According to Rogers' (1995) theory of innovation, innovators are those people who not only have the intention to adopt a new technology, but actually are ready to take the risk by being the first to purchase it. They are the customers who "decide to adopt an innovation independently of the decisions of other individuals in a social system" (Demand Forecasting, 2017; Lafferty and Goldsmith, 2004). Innovation literature has argued that customers will consider a product to be innovative if the product has the following five characteristics: relative advantage, compatibility, complexity, costs, and observability (Rogers, 1995 and 1983). If customers perceive the innovative product to be useful, then at least the first 2.5% of the customers who are considered to be *innovators* (Rogers, 1995) will have the intention and readiness to adopt and purchase new technological products. In alignment with the above result, Thompson *et al.* (2006) in their recent study posited that customers' personal innovativeness plays an important role in explaining intentions to use information technology. Therefore, marketers have been interested in those individuals who enjoy trying new products (e.g., innovators) because "they are most likely to enhance the diffusion of the new products (e.g., Lafferty and Goldsmith, 2004, p. 26)

The diffusion model (Bass, 1969), also known as the growth model, has indicated that the speed of adoption of new technology depends on how customers perceive it. If the new technological product is perceived by customers to have characteristics noted by Rogers (1995), the speed of adoption of the technology should be accelerated (Bass, 1969). Diffusion model helps in the understanding of the initial purchase (adoption) of the product (Mahajan *et al.*, 1995). This leads to the following hypotheses:

H2: *Innovators, compared to all other consumers, have greater intention to adopt a new technological product.*

H3: *Innovators, compared to all other consumers, are more likely to actually adopt a new technological product.*

C. Tech-Knowledge and Tech-Apprehension to Technology Adoption Intention

Tech-familiarity and/or *tech-knowledge* is defined as a customer's skill and/or expertise in using the technology. In other words, it is defined as a customer's awareness of the presence of new technological products in the market. For example, if the customer is knowledgeable and somewhat familiar with new technology, such as a TReO, then he/she will have some intention to use the technology in the future. Chen and He (2003), in the context of online retailing, have empirically shown that customers' knowledge about the brand is positively related to their intention to adopt an online retailer. It is because of familiarity with the brand that risk uncertainty of the retailer was decreased.

Studies in the context of online shopping have indicated that "consumers – particularly inexperienced surfers – worry about what might happen if they send their credit card data over the internet. The obstacle cited most often by merchants and consumers alike is fear" (Chen and He, 2003, p. 677). Apprehension or fear of disclosing credit card information online reduces inexperienced surfers willingness to shop online. A past study by Alba and Chattopadhyay (1985) indicted the importance of customer knowledge about the product and its impact on the customer's decision-making process. As Rossiter and Percy (1987) have mentioned, familiarity and/or knowledge about the brand enhances customer brand identification ability under different conditions due to the *trace* of the brand in memory. In the context of medical science, a seminal study by Gaggioli *et al.* (2005) posited physicians' current telemedicine technology knowledge to have a positive impact on their intention to use telemedicine. Similarly, in this study, it can be said that customers' knowledge about the new technology will reduce their apprehension, which in turn will enhance their intention to adopt the new technology. Thus, we posit the following hypotheses:

H4: *Customer familiarity and/or knowledge about new technology are positively related to adoption intention.*

H5: *Customer familiarity and/or knowledge about new technology are inversely related to technology apprehension.*

H6*: Customer apprehension in using technology is inversely related to technology adoption intention.*

H7: *Customer apprehension in using new technology is inversely related to the chance of actual technology adoption.*

D. Technology Adoption Intention to Technology Adoption

We have *defined technology adoption intention*, in this study, as the customers' determination/endurance to use the technology in the future. Our definition of technology adoption intention is in line with the definition as given by Kumar *et al.* (2003). According to Kumar *et al.* (2003), intention is defined as a customer's willingness to engage in a relationship. Two important theories in the social psychology literature, specifically theory of planned behavior (Azjen, 1991) and theory of reasoned action (Fishbein and Azjen, 1975), have shown customer intention toward a behavior to be the predictor of actual occurrence of the behavior. These findings are consistent with the findings of several other studies in the domain of technology acceptance, whereby researchers have indicated customer intention to adopt a technology to be the antecedent of technology adoption (e.g., Venkatesh *et al.*, 2003; Davis *et al.*, 1989). Besides the above studies there is research in the information systems and other disciplines which have indicated intention to be the dependent variable of behavior (e.g., adoption) (see Venkatesh *et al.*, 2003; Azjen, 1991; Sheppard *et al.*, 1988). Thus, we hypothesize:

H8: *Customer technology adoption intention is positively related to actual adoption of new technology.*

IV. Methodology

To test the proposed framework, measured items were created to tap the underlying six constructs used in this study. First, the instrument was pre-tested and once the instrument was finalized, data were collected from business undergraduate students at a Midwestern university. Two hundred and thirty-five questionnaires were distributed and collected; one questionnaire could not be used due to missing or incomplete data. More than 51% (n = 120) of the subjects used in this study were female. Approximately 91% (n = 213) subjects were below 24 years and 67.9% (N=159) had a household income below $10,000. About 73.1% (n = 171) were Caucasian, while the remaining 26.9% (n = 73) belonged to other ethnic groups. The demographic characteristics were expected based on the use of a homogeneous convenience sample.

A. Item Measurement

All together 21 items were used to measure the six underlying constructs [attitude (ATT), innovator (INN), technology knowledge (TECK-KNOW), technology apprehension (TECH-APP), technology adoption intention (TAI), and technology adoption (TA)]. (See Appendix A). As suggested by Hair *et al.* (1998), construct reliability for all these constructs was calculated. Results indicated that the construct reliability for all of the six constructs was in the range of 0.701 to 0.933.

B. Model Evaluation

EQS 6.1 was used to conduct structural equation modeling using a two-stage analysis, with raw data as input. A two-step process of structural equation modeling, measurement model and structural model, was used for model evaluation (Anderson and Gerbing, 1982).

B.1 Measurement Model:

Confirmatory factor analysis (CFA) was used to ensure reliability and validity of the six underlying constructs. The results of the CFA indicated that the normalized estimate of multivariate kurtosis was 17.71, which exceeded the recommended cutoff point of 3. As suggested by Bentler (1990a; 1990b) if the normalized estimate of multivariate kurtosis is greater than the recommended cut-off point then the researcher should use a robust maximum likelihood (ML) estimation method. This provides more accurate and reliable information than the standard ML method. Finally, each construct was assessed for unidimensionality, reliability, convergent, and discriminant validity (see tables 2 and 3).

B.2 Unidimensionality and Reliability

The standardized loadings of all the items measuring the six underlying constructs were found to be in the range of 0.576 to 0.941; hence, meeting the threshold of unidimensionality, which is above 0.50 (Bollen, 1990). According to Hair *et al.* (1998) "reliability is a degree of internal consistency of the construct indicators," therefore, "the more reliable measures such as composite reliability and average variance extracted (AVE) provide researchers with greater confidence that the individual indicators are all consistent in their measurement" (p. 612). Results indicated that the composite and/or construct reliability for all the constructs were above 0.701. Thus, indicating that the indicators of the six underlying constructs were valid and accurately measure the underlying constructs (see Table 1).

Table 1: Measurement Model, Reliability, and Average Variance Extracted Result

Construct	Items	Standardized Loadings	*t*-value*	S.E.	Construct/ Composite Reliability	Average Variance Extracted (AVE)
Attitude (ATT)	ATT 1 ATT 2 ATT 3	0.873 0.941 0.910	n/a 9.962* 10.211*	n/a 0.129 0.123	0.933	0.823
Innovator (INN)	INN 1 INN 2 INN 3	0.720 0.837 0.708	n/a 5.993* 5.939*	n/a 0.241 0.159	0.802	0.576
Technology Knowledge (TECH-KNOW)	TECH-KNOW 1 TECH-KNOW 2 TECH-KNOW 3	0.677 0.816 0.811	n/a 5.743* 6.421*	n/a 0.419 0.433	0.815	0.597
Technology Apprehension (TECH-APP)	TECH-APP 1 TECH-APP 2 TECH-APP 3 TECH-APP 4 TECH-APP 5	0.637 0.775 0.747 0.784 0.574	n/a 6.288* 6.598* 6.572* 5.739*	n/a 0.216 0.214 0.198 0.208	0.833	0.502
Technology Adoption Intention (TAI)	TAI 1 TAI 2 TAI 3 TAI 4	0.880 0.901 0.878 0.666	n/a 10.502* 9.363* 6.977*	n/a 0.107 0.107 0.098	0.902	0.700
Technology Adoption (TA)	TA 1 TA 2 TA 3	0.761 0.643 0.576	n/a 3.047* 1.845*	n/a 0.109 0.139	0.701	0.443

Convergent validity helps ensure that the concepts that should be related theoretically are actually related. According to Fornel and Lacker (1981a and 1981b) convergent validity exists if the loadings and AVE estimates are higher than the recommended cut-off value. The results indicated in Table 2 illustrate that all of the constructs under investigation surpass the acceptable level, showing good convergent validity. *Discriminant validity* conveys the degree to which concepts that should not be related theoretically are, in fact, not related (Campbell and Fiske, 1959). Discriminant validity is shown when the correlation between any two constructs is less than the square root of the AVE and when the items measuring the construct in the diagonal elements of the matrix are greater than corresponding off-diagonal elements. Table 2 shows evidence of discriminant validity among the present constructs.

Table 2: Mean, Standard Deviation, Convergent and Discriminant Validity Matrix

Construct	**Mean**	**Standard Deviation**	ATT	INN	TECH-KNOW	TECH-APP	TAI	TA
ATT	4.690	1.197	**0.907**	-0.161	0.155	-0.198	0.143	-0.003
INN	2.271	0.820		**0.759**	-0.514	0.417	-0.091	0.085
TECH-KNOW	3.807	0.755			**0.773**	-0.352	0.171	-0.080
TECH-APP	2.131	0.651				**0.708**	-0.147	0.122
TAI	4.198	0.671					**0.837**	0.065
TA	4.190	0.559						**0.665**

ATT = Attitude; INN = Innovator; TECH-KNOW = Technology knowledge; TECH-APP = Technology apprehension; TAI = Technology adoption intention; TA = Technology adoption.

Besides assessing the unidimensionality, reliability, convergent, and discriminant validity, the overall fit of the proposed model was also assessed. The CFA analysis result indicated that the Satorra-Bentler Scaled Chi-Square index (S-Bχ2) was significant (S-Bχ2 = 261.605, df = 182, $p > 0.0001$). Past studies by Bagozzi and Yi (1988) and Byrne (1994) have shown Chi-Square index to be sensitive to sample size; hence, alternative fit indices were also taken into consideration (Baumgartner and Homburg, 1996).

The alternative fit indices indicated that the data closely fit the model with Root Mean Square Error of Approximation (RMSEA) of 0.051 (Browne and Cudeck, 1989). Other fit indices, such as Bentler's (1990b) Comparative Fit Index (CFI) of 0.937, Bentler and Bonnet's (1980) Non-Normed Fit Index (NNFI) of 0.927 and an incremental fit index (IFI) of 0.938, were all higher than the acceptable fit threshold of 0.90 to indicate good fit (Hair *et al.*, 1998). Indices for the proposed model are summarized in Table 3.

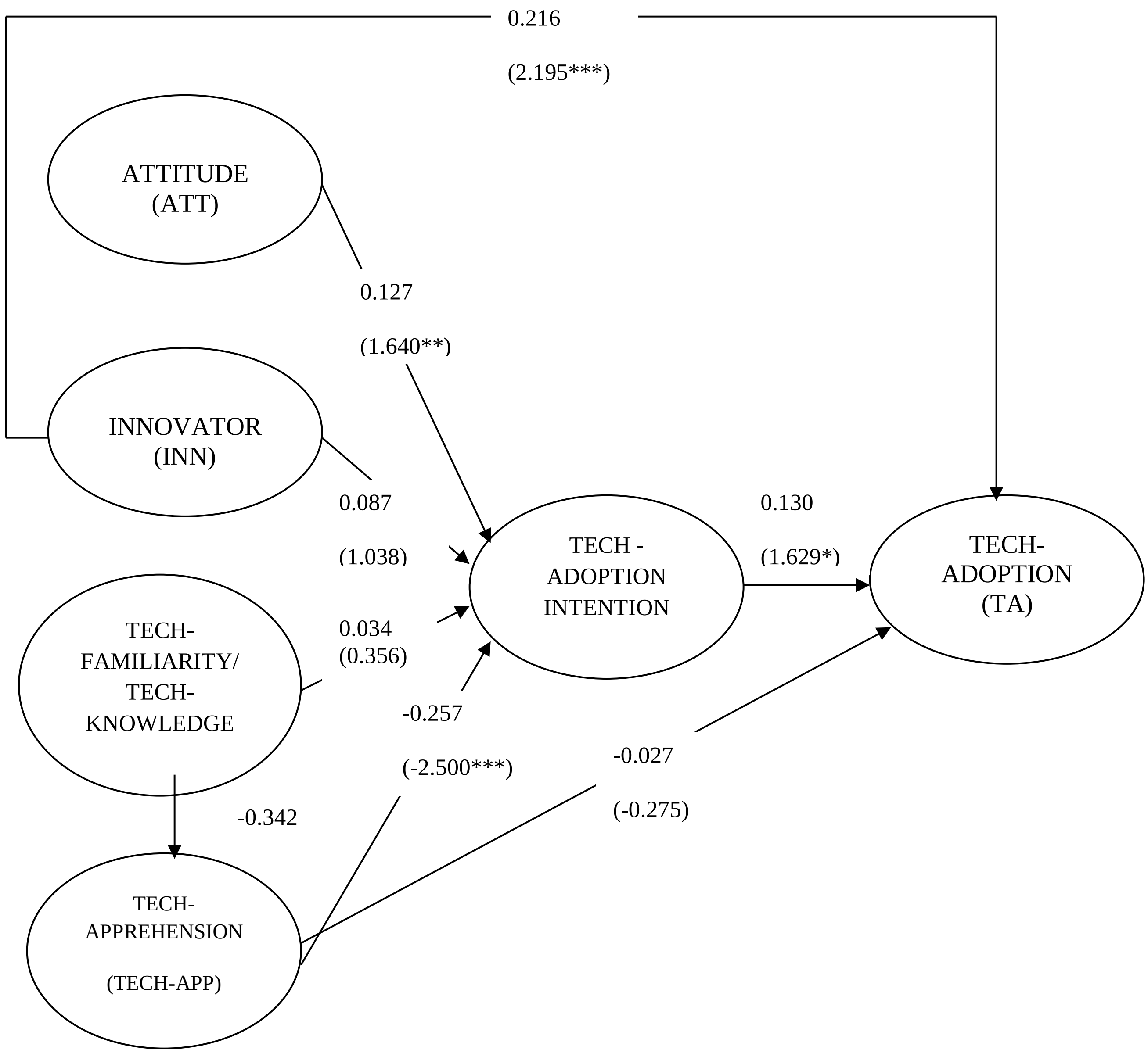
Table 3: Model Fit Indices – For The Proposed Model

Fit Indices	Acceptable Fit Thresholds	Fit Indices of Proposed Model
χ^2 / df	≤ 3	1.445
RMSEA	≤ 0.08	0.051
CFI	> 0.90	0.937
NFI	> 0.90	0.824
IFI	> 0.90	0.938
NNFI	> 0.90	0.927
90% CI of RMSEA	Between 0 and 1	(0.036, 0.064)

B.3 Structural Model

In the structural model eight hypothesized paths between the six underlying constructs were tested for significance. Figure 2 shows the structural model result. Results indicated that out of the eight paths five were significant.

Figure 2: Result of the Proposed Model



* p < 0.15; ** p < 0.10; *** p < 0.05; **** p < 0.01

Fit Indices of Proposed Model

RMSEA =	0.051
CFI =	0.937
NNFI =	0.927
IFI =	0.938
S-B $\chi 2$ =	261.605

V. Results

EQS results for the proposed structural model indicated that customer attitude toward technology (ATT) was a significant predictor of customer technology adoption intention (TAI) with a standardized path coefficient of 0.127, $p < 0.10$. Therefore, *Hypothesis 1* is *supported*. However, innovativeness (INN) was not an antecedent of technology adoption intention (TAI), providing *no support* for *Hypothesis 2*. Innovativeness (INN) was found to be a significant predictor of technology adoption (TA) (standardized path coefficient of 0.216, $p < 0.05$), which *supported Hypothesis 3*. Results also indicated that technology familiarity/ knowledge (TECH-KNOW) was not a predictor of technology adoption intention (TAI), providing *no support* for *hypothesis 4*. However, it was found to be a significant predictor of technology apprehension (TECH-APP) (standardized path coefficient of -0.342, $p < 0.01$) and was in the expected direction, *supporting Hypothesis 5*.

This study also indicated that technology apprehension (TECH-APP) was an antecedent of technology adoption intention (TAI) (standardized path coefficient of -0.257, $p < 0.05$), but not a predictor of technology adoption (TA). Therefore, *support* was found for *Hypothesis 6* but *not for Hypothesis 7*. However, technology adoption intention (TAI) was a significant predictor of technology adoption (TA) (standardized path coefficient of 0.130, $p < 0.15$), supporting *Hypothesis 8*.

To test if technology adoption intention (TAI) mediates the relationship between innovator (INN), technology apprehension (TECH-APP) and technology adoption (TA), multiple regression was used. To test the mediation effect, as suggested by Baron and Kenny (1986), the dependent variable (technology adoption) was regressed on the independent variables (innovator and technology apprehension). As posited, results indicated that technology adoption intention (TAI) fully mediated the effect between INN and TA ($\beta = 0.041$, $t = 0.550$, $p = 0.583$; ns). TAI was also found to mediate the relationship between TECH-APP and TA ($\beta = 0.105$, $t = 1.390$, $p = 0.116$; ns). Additionally, technology apprehension (TECH-APP) fully mediated the relationship between technology familiarity/knowledge (TECH-KNOW) and technology adoption intention (TAI). Thus, our results indicated that the relationship between innovator (INN) and technology adoption (TA) is direct as well as it is also mediated through technology adoption intention (TAI).

A. Model Comparison

To see if the fit indices of the proposed model can further be improved, a nested model test was performed. In the nested model approach, the number of constructs and indicators remains constant, but the number of estimated relationships changes.

As suggested by the Wald test, the most non-significant path (e.g., path from TECH-APP -> TA) in the proposed model was deleted to see if there is any improvement in the fit indices compared to the proposed model. Results indicated that there was no statistically significant change in the Satorra-Bentler Scaled Chi-Square (Δ S-Bχ2) value between the proposed model and Nested Model 1 (model after deleting the path from TECH-APP -> TA). Hence, Nested Model 1 was better than the proposed model. Then again as suggested by Wald statistics, the non-significant path from TECH-KNOW to TAI was deleted and Nested Model 1 was compared with Nested Model 2 to see the improvement in fit indices. Results indicated no significant difference between Nested models 1 and 2. Hence Nested Model 2 was considered over Nested Model 1.

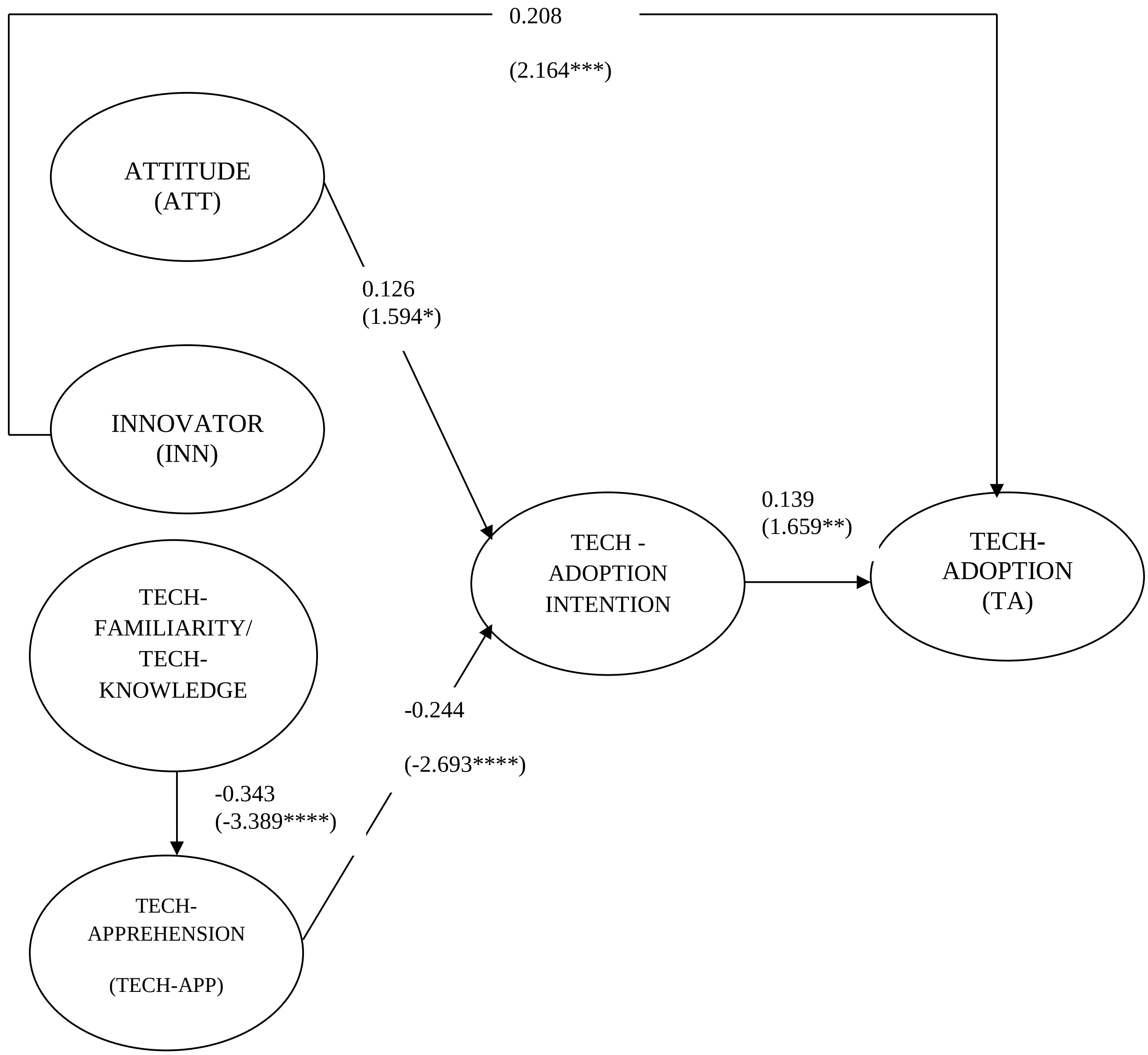
Finally, the non-significant path between innovators to technology adoption intention was also deleted, as recommended by the Wald test. The nested model comparison results indicated that the change in the Satorra-Bentler Scaled Chi-Square (Δ S-Bχ2) between Nested Model 2 and Nested Model 3 at 1 degree of freedom was less than the critical value of 3.84. Hence Nested Model 3 was considered as the final model (Figure 3) because it is the most parsimonious.

Table 4: Nested Model Result

Model	**Satorra-Bentler Scaled Chi-Square Index**	**Degrees of Freedom**	**Change in the Satorra-Bentler Scaled Chi-Square (Δ S-Bχ2)**	**Change in Degrees of Freedom (Δdf)**	**Sig. (p)**
Proposed	261.605	181			
Nested 1	261.594	182	Δ S-Bχ2 = S-Bχ2 $_{(Nested1)}$ – S-Bχ2 $_{(proposed)}$ = 0.011	Δ df = df$_{(Nested\ 1)}$ – df $_{(proposed)}$ = 1	n.s.
Nested 2	261.737	183	Δ S-Bχ2 = S-Bχ2 $_{(Nested\ 2)}$ – S-Bχ2 $_{(Nested\ 1)}$ = 0.143	Δ df = df$_{(Nested\ 2)}$ – df $_{(Nested\ 1)}$ = 1	n.s.
Nested 3	262.419	184	Δ S-Bχ2 = S-Bχ2 $_{(Nested\ 3)}$ – S-Bχ2 $_{(Nested\ 2)}$ = 0.682	Δ df = df$_{(Nested\ 3)}$ – df $_{(Nested\ 2)}$ = 1	n.s.

n.s. = Non-significant

Figure 3: Final Model Result of Nested Model 3



* p < 0.15; ** p < 0.10; *** p < 0.05; **** p < 0.01

Fit Indices of Nested Model 3

RMSEA =	0.050
CFI =	0.939
NNFI =	0.930
IFI =	0.940
S-B $\chi 2$ =	262.419

VI. Managerial Implication, Limitation, and Future Research

The technology acceptance model and diffusion of innovation theory have identified ease of use, compatibility, relative advantage, and complexity (Kleijnen *et al.*, 2004; Venkatesh *et al.*, 2003; Plouffe *et al.*, 2001; Karahanna *et al.*, 1999; Rogers, 1995) as the important factors that help explain the adoption of high technology products. However, our study extends the above theories by emphasizing that the customer's attitude, innovativeness, familiarity/knowledge about new technology, and technology apprehension should also be given attention by managers in order to increase customer willingness to adopt high technology products, which leads to actual adoption.

Results of our study indicated that customer positive attitude toward a high technology product is a significant predictor of customer technology adoption intention. Customer technology familiarity/knowledge helps in reducing customers' apprehension in using the technology; however, it may not have a direct effect on technology adoption. Our research suggests that the relationship between technology familiarity and adoption intention is fully mediated through customer technology apprehension. In other words, if a customer is familiar and knowledgeable about the high-technology gadgets, they will have less fear in using them. The reduced fear will enhance their willingness to adopt such "gifted innovation." Thus, it may be said that to increase customer adoption of high-technology products, managers should try to change the customer's mindset about the high-technology products by increasing familiarity/knowledge. Product familiarity/knowledge can result from advertising the benefits that the customer can derive from the products, increasing trial through instore displays, or by the use of realistic and prominent product placements. If customers are familiar with the high-technology products they will perceive the gadgets to be easy to use and useful, reducing their fear of using the high-tech products. Our study shows that this reduced fear may enhance overall intention to adopt the technology.

From our results, it may also be said that to increase the sales of high-technology products, managers should try to identify those customers who are innovators. Innovators perceive a high-technology product to be new and relevant and are ready to experiment with the new technology by actually adopting them. Furthermore, our results indicated that customer positive intention to adopt is an enabler for actual adoption of new technology. Thus, managers should try to find a way to increase customers' adoption intention to use a high-technology product because if a customer has a positive intention to adopt a technology then it is most likely that they will adopt the technology.

Some of the limitations of our study, which evoke opportunities for future research, are as follows: (1) A convenience sample of university business students was used in this study. (2) Participants for this study were only those who owned or had used high-technology products. Future research should be carried out to see what prevents other customer from adopting the high-technology products; (3) Sample size limited our ability to validate the findings by split sample, which leaves scope for validation of the final model.

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Appendix A

Items Used to Operationalize Constructs

Attitude (7-points scale) (Construct reliability = 0.923; AVE = 0.823)

Would you say your attitude toward new technology such as cell phones, PDA, etc. is:

ATT1	bad	--	--	--	good
ATT2	unfavorable	--	--	--	favorable
ATT3	negative	--	--	--	positive

Innovator (5-point scales anchored by totally disagree and totally agree) (Construct reliability = 0.802; AVE = 0.576)

INN 1	I experiment with new technologies.
INN 2	I like to be among the first to try new technologies.
INN 3	I seek information about new devices.

Tech-knowledge/Tech-familiarity (5-point scales anchored by strongly disagree and strongly agree) (Construct reliability = 0.815; AVE = 0.597)

How knowledgeable are you in using technology such as cell phones, PDA, etc.?

TECH-KNOW 1	I feel I am quite familiar with using a cell phone.
TECH-KNOW 2	Among my circle of friends, I am one of the “experts” in using cell phones.
TECH-KNOW 3	I know a lot about cell phones.

Tech-Apprehension (5-point scales anchored by totally disagree and totally agree) (Construct reliability = 0.833; AVE = 0.502)

TECH-APP 1	I have difficulty understanding most technological matters.
TECH-APP 2	When given the opportunity to use some form of technology, I fear that I might damage it in some way.
TECH-APP 3	Technological terminology sounds like confusing jargon to me.
TECH-APP 4	I have avoided technology because it is unfamiliar to me.
TECH-APP 5	I am unable to keep up with important technological advances.

Tech-Adoption (5-point scales anchored by completely unimportant to completely important) (Construct reliability = 0.701; AVE = 0.443)

Important reasons for adopting new technology such as cell phones, PDA, etc. are:

TA 1	Ease of use
TA 2	Security
TA 3	Cost

Tech-Adoption Intention (5-point scales anchored by strongly disagree and strongly agree) (Construct reliability = 0.902; AVE = 0.700)

How willing you are to use technology such as cell phones, PDA, etc. in the future (continue to use OR begin to use).

TAI 1	Once I have accepted usage of a cell phone, I will certainly use it in the future.
TAI 2	Once I use a cell phone, I will certainly use it in the future.
TAI 3	Once I have gained experience in using a cell phone, I will most probably use it in the future.
TAI 4	I will enjoy using a cell phone in the future.

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Understanding the Role of Blogger Recommendations on Consumer Purchasing Behavior

By DHOHA ALSALEH*

This study examines the influence of the perceived usefulness of blogger recommendations, the blog reader's confidence in them, and the reputation of bloggers on consumers' purchasing attitudes and intentions. A model is proposed, based on the theory of reasoned action (TRA) and the technology acceptance model (TAM) empirically examined with a primary dataset of 439 blog readers in Kuwait. Perceived usefulness of blogger recommendations, confidence, and reputation had influential effects on blog users' purchasing attitudes and intentions. Confidence in bloggers significantly influences perceived usefulness of blogger recommendations. The reputation of bloggers had a significant positive direct effect on confidence in bloggers.

Keywords: Blog, Attitude, Consumer Behavior, Perceived Usefulness, Recommendations

JEL Classification: D00, D01, D02, D03, D04

I. Introduction

Blogging is considered a leading online medium that influences the purchasing decisions of people globally (Schroeder, 2014). Consumers are technologically enabled and informed on the practicality in their purchasing decisions (Cina, 1989). The consumer and seller association is constantly changing with greater technological empowerment on both sides. These factors have fundamentally changed consumer expectations, motivated demand for improvements, developed more personalized and innovative products, and resulted in better experiences and services. Consumers seek experiences that are personalized to their individual needs while shopping. In today's retailing era, creating and maintaining a superior consumer experience are identified as the main objectives of many firms (Hong, 2015).

Information delivery sources have significantly changed along with the technological empowerment by the internet. It has been demonstrated that consumers usually trust bloggers and reviewers more than salespeople and corporations. Bloggers have become reliable online presenters due to their sustained efforts in several fields (Hsu *et al*., 2010). Bloggers are likely to use information suggested by the associated consumers to evaluate the services or products before they make a purchasing decision (Al-Haidari, 2016). Web 2.0 tools can be used by consumers to share their experience and information, and to purchase across several platforms, including online

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communities, websites, personal blogs, and independent websites. Whenever online consumers share experience-based information on a specific product, other consumers can review their input to assess the attributes of a product before purchasing it (Elmorshidy *et al*., 2015).

In recent years, blogging has been considered to be the most common and prominent platform for recording and presenting ideas and reactions related to any specific life event (Hsu *et al*., 2013). It has been observed by Singer (2009) that an average of 900,000 news articles are being posted daily on blogs. In particular, people blog their comments frequently after using any product or service to share their views with others. Wegert (2010) indicated that 81 percent of consumers seek recommendations from bloggers before purchasing any product through an online website. 74 percent of the people who had taken the recommendations and advice found them influential in purchasing any product or service. Consequently, blogging has evidently become an important factor for consumers before they purchase products or services and make purchasing decisions.

In recent years, blogging has been developed as a popular media source for sharing thoughts, feelings, and ideas linked to particular events. People share their personal experiences such as traveling or hobbies on a personal website, and also share their reviews after using products. While the literature related to the impact of blogging is growing at this time, an understanding of the impact of blogging is still under-documented in Arab countries (Rouibah, 2014). The main objective of this study is to understand whether trust in the blogger, reputation of the blogger, and belief in blog usefulness influence Arab consumers' purchasing attitudes and intentions.

This study has combined the theory of reasoned action (TRA) (Fishbein and Ajzen, 1975) with the technology acceptance model (TAM) (Davis, 1989) to understand factors that influence consumer attitudes toward blogger recommendations. While TRA has been highly influential in explaining attitude-intention-behavior relations, TAM was specifically designed to predict and explain a user's acceptance of an innovative information system. TAM theorizes that an individual's behavioral intention to adopt a particular piece of technology (blogs) is determined by the person's attitude toward the use of the technology. Attitude, in turn, is determined by two beliefs: perceived usefulness and perceived ease of use. On the other hand, TRA is an intention model from social psychology that is concerned with the primary determinants of behavior (Ajzen and Fishbein, 1980; Fishbein and Ajzen, 1975). According to TRA, attitude toward the behavior is determined by the person's salient beliefs about the consequences of performing the behavior multiplied by the evaluation of those consequences. Subjective norms have to do with one's perceptions that referent groups and individuals believe certain behaviors should or should not be performed (Fishbein and Ajzen, 1975).

The current study has used elements from both TRA and TAM because TAM alone fails to take into account other important characteristics of bloggers. For example, TAM assumes that information systems are used in organizational settings to improve the efficiency of workers. It excludes the fact that information systems could be used outside organizational settings by individual users, and such usage can also be influenced by other users. TAM does not address the roles of other users in influencing an individual's attitude toward bloggers, and consequently the usage intention. This is problematic, since numerous psychological studies prove that individuals' behavior is influenced by the behavior of other people surrounding them. Therefore, current research builds upon previous studies of TAM and TRA to explain consumer attitudes toward blogger recommendations to purchase products and services.

Many studies have comparatively demonstrated that blogger recommendations would have a strong and influential effect on marketing to consumers (Pavlou, 2003; Chau *et al*., 2007). Consumers have been observed to believe that blogs are more trustworthy as compared to traditional media (Johnson and Kaye, 2009). The findings are expected to facilitate and clarify the most effective marketing strategies for targeting Arab customers and promoting products and services in Arab regions. It is expected that blogger recommendations are likely to assist Arab consumers in their purchasing decisions, and the result may also contribute to providing assistance to marketing managers. This study is organized as follows: Section II provides the theoretical framework of the research and develops the research hypotheses; Section III describes the research methodology; Section IV provides the results of the study; Section V provides discussion and conclusion of the study and Section VI discusses limitations and future research.

III. Theoretical Framework and Research Hypotheses

Blogging consists of the writer's comments, brief texts, images, and links structured in sequential order. As mentioned by Zhao and Kumar (2013), over 1.2 million users post blogs every day through the communication procedures that interchange comments between several different blogs. In comparison to the activities related to blogging, micro-blogging can be considered as a quick and easier way to communicate short messages from a mobile device or computer. The use of micro-blogging has been found increasing to 62 percent between the years 2009-2011. Twitter, Instagram, and Facebook can be considered as examples of micro-blogging tools.

Mikalef *et al*. (2013) have discussed consumers' perceptions of social media. A theoretical framework has also been suggested by Hsu and Tsou (2011) that outlined the association among consumer experience, purchasing intention, and information credibility in the blogging environment. The study indicated that customer experiences have a significant influence on purchasing intentions due to information accountability. Hence, information accountability may be crucial for enhancing consumer experiences, which is essential to strengthening purchasing intentions.

Hsu *et al.* (2013) have examined the effects of blogger recommendations on the purchasing attitudes of customers and analyzed the level of trust that consumers have in blogger suggestions for specific products and services. The results indicate that there is a significant persuasive effect on the purchasing behavior of online consumers based on the perceived usefulness of a blogger's suggestions and trustworthiness.

A significant literature has examined the impact of blogger recommendations on consumer purchasing attitudes and intentions in Western countries (Goldsmith and Horowitz, 2006; Riegner, 2007); however, limited research has been conducted to examine the influence of blogger recommendations in Arab countries (e.g., Kuwait) (Al-Roomi, 2007; Riquelme and Saeid, 2014). It can be argued that what is effective in non-Arab countries may or may not be effective in Arab countries due to the cultural and social environment. Factors such as language, religion, education, social norms, tradition, morale, social class structure, social diversity, pattern of living (e.g., Bedouin, rural, and urban), expressiveness and social interaction, family, and group relations are a few examples of how/why peoples' behavior may vary from culture to culture (Ein-Dor *et al*., 1993; Barakat, 1993; Hofstede, 1984). Moreover, Barakat (1993) identified a number of value orientations that indicate the complexity and contradictory nature of comparing developed countries with less developed countries such as Arab countries (e.g., past oriented/future oriented, conformity/creativity, collectivity/individuality, open/closed mindedness, and culture of the mind/culture of the heart).

Arabs use different social media sites to generate information and share ideas (Kaplan and Haenlein, 2010). For example, across the Arab world, there are over 1.3 million active Twitter users; Kuwait reached 8 percent among Arab nations, ahead of Bahrain at 4 percent, Qatar at 2 percent, the UAE at 2 percent and Saudi Arabia at 1 percent. Also, data show that Arab nations mostly use Facebook and Instagram in social media channels (87 percent and 84 percent, respectively) (*Arab Social Media Report*, 2015). Other reports indicate that 70 percent of Kuwait youth have been found to actively participate in social network sites (*Arab Youth Survey*, 2010), and that the youth of Kuwait have been described as Internet active (Wheeler, 2001 and 2003). Moreover, Kuwait has the highest percentage of social media users in the Middle East (*Kuwait News*, 2013).

In the current research, the role of blogger recommendations on consumer purchasing behavior has been investigated in a smaller platform in Kuwait. It is expected that blogger recommendations would be useful for analyzing consumers' buying behavior in Kuwait. However, no research has yet been conducted to investigate the factors influencing consumer purchasing reactions to blogger recommendations. Therefore, this study aims to explore the factors that can affect consumer purchasing attitudes and intentions, taking into consideration the influence of blogger recommendations.

A. Research Hypotheses

The study examines the role of the following key constructs to evaluate the impact of blogger recommendations (see Figure 1).

A.1 Perceived Usefulness of Blogger Recommendations

Perceived usefulness is defined as the extent to which a person believes that using a technological innovation will enhance his/her job performance (Davis *et al*., 1989). In the blogging context, this study redefined perceived usefulness as the degree to which a blog reader believes that blogger recommendations and reviews would enhance his/her buying decision, particularly when purchasing expensive, new, or complex products. A common explanation states that buying expensive, new, or complex products would create uncertainty; individuals are generally uncomfortable with uncertainty and will tend to refer to blogger recommendations for support in reducing the risks of their buying decisions (Burkhardt and Brass, 1990; Brown and Reingen, 1987; Kotler and Makens, 2010). It goes back to the theory of reasoned action (TRA), in which an individual may develop beliefs by referring to information from or normative practices of a group and peers. Consequently, these beliefs will influence individual behavioral intention.

Examining the literature on consumer behavior shows that reference groups influence consumer purchasing behavior (Bearden and Etzel, 1982; Childers and Rao, 1992; Engel *et al*., 1995). Many other previous studies have empirically confirmed that perceived usefulness has significant effects on attitude and intention (Hsu and Lu, 2004; Lin and Lu, 2000; Yu *et al*., 2005). Accordingly, the following hypotheses are proposed:

H_1: *Perceived usefulness of blogger recommendations will positively affect blog readers' attitudes toward purchasing products/services.*

H_2: *Perceived usefulness of blogger recommendations will positively affect blog readers' intentions to purchase products/services.*

A.2 Trust

Trust (T) can be defined, in general terms, as being a firm reliance on the integrity, ability, or character of a person or thing (Gefen, 2002; McKnight *et al*., 2002a). In the blog context, trust is defined by Doney and Cannon (1997) as "perceived credibility and benevolence of a target of trust (i.e., the other party: in this study, the target of trust is the blogger)". This definition of trust is relevant to an online (blogging) context. Trust issues have emerged as major consumer concerns. Blogs are considered by online users as a highly credible source amongst all sources in different media (Johnson and Kaye, 2009). In addition, previous studies indicate that trust is an important factor for successful online transactions (Salo and Karjaluoto, 2007), and is also a key for attracting and retaining customers and obtaining competitive advantage on the internet (McKnight *et al*., 2002b).

A careful review of the literature reveals several influences of trust on consumers. For example, previous studies have confirmed that trust is strongly associated with attitude and purchasing behavior in online transactions (Kuan and Bock, 2007; Pavlou, 2003). Similarly, past studies have empirically verified that trust significantly affects attitudes of consumers (Suh and Han, 2002; Wu and Chen, 2005). Moreover, studies such as Lim *et al*. (2006) and Hsiao *et al*. (2010) also noted that trust positively influences consumers' attitudes and shopping intentions. Therefore, bloggers are needed to provide trust-related mechanisms to encourage blog readers to adopt blogger recommendations.

A stable and consistent review along with recommendations, continuous interaction between the blogger and blog readers, unambiguous and clear reviews, and knowledgeable blogs are some of the practices required to build the blog reader-blogger trust relationship. Moreover, trust typically grows with shared experience, shared friends, and interactions among others over a period of time (Swamynathan *et al.*, 2008). The literature reveals that the relationship between trust and perceived usefulness is also positive, and that trust increases certain features of perceived usefulness (Gefen *et al.*, 2003). The indirect effect stems from the fact that trust could influence attitudes towards social media usage via perceived usefulness, thus reducing risks and increasing trust and, consequently, users' attitudes and intentions (Han and Windsor, 2011). Consequently:

H_3: *Trust will positively affect blog readers' perception of usefulness.*
H_4: *Trust will positively affect blog readers' attitudes toward purchasing products/services.*
H_5: *Trust will positively affect blog readers' intentions to purchase products/services.*

A.3 Reputation

In the blog context, reputation is related to the extent to which a blogger is credible (Burgess *et al*., 2009). Therefore, this study suggests that bloggers with different levels of reputation will influence blog readers' attitudes and behavioral intentions differently. For example, a highly reputable blogger may become an opinion leader influencing others to purchase products/services through a persuasive message that will influence the reader's confidence in a specific product/service (Shamdasani *et al*., 2001).

An examination of the literature reveals that many studies have investigated the importance of reputation as an antecedent of trust or behavioral intention. For example, some studies empirically verified that reputation significantly affects trust or behavioral intention (Casalo *et al*., 2008; Keh and Xie, 2009; Koufaris and Hampton-Sosa, 2004). Moreover, prior studies have shown that consumers are dependent on information provided by reputable sources in the process of decision making (MacKenzie and Lutz, 1989). Reputable recommendations by bloggers depend on the social capital perspective in which a blogger with good online social relations can establish a positive reputation. The positive reputation of a blogger may positively influence blog readers' attitudes and purchasing behavior (Hung and Li, 2007). This is due to the fact that the blogger's reputation, as a basis of credibility, is considered as a persuasive factor in convincing a consumer to purchase a certain product/service. Therefore, the following hypotheses are proposed:

***H_6*:** *Reputation of a blogger will positively affect blog readers' trust in the blogger.*
***H_7*:** *Reputation of a blogger will positively affect blog readers' attitudes toward purchasing products/services.*
***H_8*:** *Reputation of a blogger will positively affect blog readers' intentions to purchase products/services.*

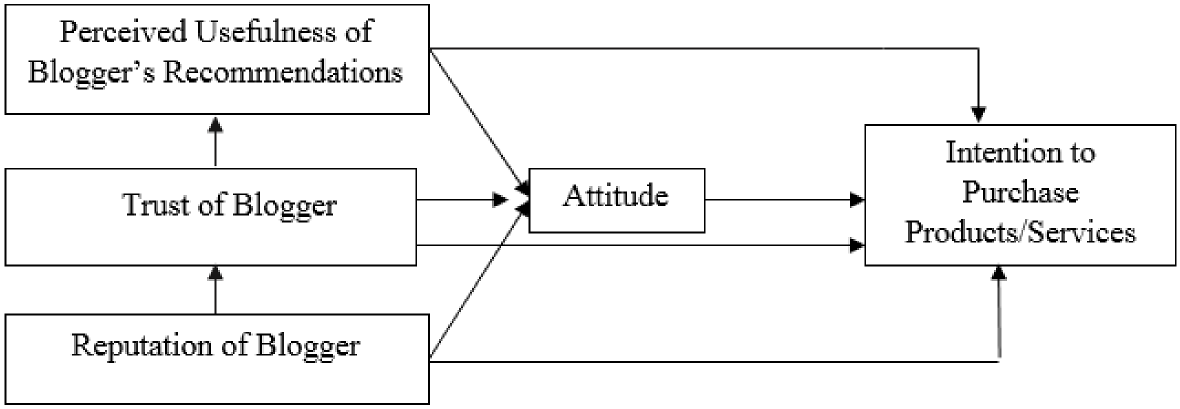
A.4 Attitudes

Attitude is central to behavioral theory and decision-making research. It is considered as one of the most significant predictors of behavior (Bagozzi, 1992). For this study, attitude is defined as the degree of a blog reader's positive feelings about purchasing products/services. The effect of attitudes on behavior intention goes back to well-known theories such as TRA, TAM, and the theory of planned behavior (TPB), which indicate that an individual's behavioral intention is influenced by his/her attitude towards the concerned behavior. Many empirical studies based on these theories have found that attitude positively affects an individual's behavioral intention (Hsu and Lu, 2007). For example, the positive effect of attitude on intention was found in the context of consumer adoption of new technology and a wide variety of innovations. It includes self-service technology (Dabholkar and Bagozzi, 2002), handheld technology (Bruner and Kumar, 2005), and smart phones (Chang *et al*., 2009). Accordingly, the following hypothesis is proposed:

***H_9*:** *Blog readers' attitudes toward products/services will positively affect their intentions to purchase products/services.*

Figure 1 illustrates the proposed and tested research model of the study. The research model hypothesized that a blog reader's intention to buy products and services is determined by attitudes about the perceived usefulness of a blogger's recommendation and the trustworthiness and reputation of the blogger. Attitude is influenced by the impact of beliefs about usefulness, trust, and reputation regarding the intention to buy products and services. In turn, the usefulness of a blogger's recommendation is influenced by trust. Additionally, trust is influenced by the blogger's reputation.

Figure 1: The Research Model



III. Methodology

A. Sample

An online questionnaire was designed on the basis of the literature and blogging practices. Data were collected from a convenience sample of undergraduate and postgraduate students from Kuwait. Students were told that their participation was voluntary, but extra credit points were offered as an inducement. A total of 521 completed questionnaires were received, but 82 respondents, who were not blog readers, were excluded from the analysis. Therefore, the study sample comprised 439 respondents. The demographic profile is presented in the following Table 1.

Table 1: Demographic Profile

Measure	Items	Frequency	Percentage (%)
Gender	Male	228	51.9
	Female	211	48.1
Age	Under 20 years	204	46.5
	20 to 25 years	214	48.7
	26 to 30 years	10	2.3
	Above 30 years	11	2.5
Amount of Reviewing Blogs for Purchasing Products/Services	1 to 3 times	48	10.9
	3 to 6 times	57	13.0
	6 to 9 times	93	21.2
	More than 10 times	241	54.9

Table 1: Demographic Profile: Continues

Experience of Reading Blogger Recommendations for Purchasing Decisions	Less than a year	124	28.2
	1 to 2 years	163	37.1
	2 to 3 years	87	19.8
	More than 3 years	65	14.8
Experience in Following Blogger Recommendations	Never	79	18.0
	Less than 3 months	127	28.9
	3 to 6 months	134	30.5
	6 to 12 months	42	9.6
	1 to 2 years	18	4.1
	More than 2 years	39	8.9
Degree of Following Blogger Recommendations	Never	93	21.2
	1 to 2 times	162	36.9
	3 to 4 times	146	33.3
	5 to 6 times	26	5.9
	More than 6 times	12	2.7

B. Scales

The online questionnaire consisted of two parts: demographic profile based on behavior towards blogging practices and constructs based on the literature. To develop scales for measuring constructs for perceived usefulness of recommendations, trust, attitude, intention and bloggers' reputations, measurement items have been utilized. These were adapted from existing validated scales from past research (Davis, 1989; Doney and Cannon, 1997; Fishbein and Ajzen, 1975; Lim *et al*., 2006), with modifications to fit with Kuwaiti culture. Each item was measured on a five-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (5). Furthermore, all survey questions, instructions, and items were translated from English to Arabic using Brislin's (1986) backward translation method.

A pre-test was performed before conducting the main survey. The pre-test included three marketing professors along with 10 undergraduate and graduate students. The purpose of the pre-test was to check the wording of the scales, the length of the instrument, and the format of the questionnaires to obtain the final version of the survey.

IV. Results

A. Descriptive Statistics

Table 2 lists the means and standard deviations of the constructs. It can be observed that, on average, the participants responded positively to the research constructs (the averages all being >3). Moreover, the coefficient α values for all constructs (except intention and blogger reputation) are above the conventional level of 0.7 (Nunnally, 1967). The scales for these constructs exhibited an acceptable level of reliability.

Table 2: Descriptive Statistics

Constructs	Means	SD	Cronbach's Alpha
Perceived Usefulness of Recommendation	3.44	0.69	0.71
Trust	3.18	0.68	0.81
Attitude	3.66	0.98	0.88
Intention	3.59	0.66	0.69
Blogger's Reputation	3.41	0.70	0.67

B. Analytical Strategy for Assessment of Model

Structural equation modeling was conducted using AMOS 22 to test the fit between the research model (Figure 1) and the data set.

C. Measurement Model

The results of the measurement model are listed in Table 3. The data indicated that the reliability of the items ranged from 0.79-0.998, which exceeds the acceptable value of 0.50 (Hair *et al*., 2006). The internal consistency of the measurement model was assessed by computing the composite reliability. Consistent with the recommendations of Fornell (1982), the composite reliability of all the items exceeded the benchmark of 0.60. The average variance extracted for all constructs exceeded the threshold value of 0.5 recommended by Fornell and Larcker (1981). Since the values of reliability were above the recommended thresholds, the scales for evaluating these constructs were deemed to exhibit adequate convergence reliability. The data in Table 4 indicate that the variances extracted by construct were greater than any squared correlation among constructs, thereby implying that the constructs are empirically distinct (Fornell and Larcker, 1981). In summary, the test of the measurement model, including convergent and discriminant validity measures, is satisfactory.

Table 3: Item Reliability, Composite Reliability and Average Variance Extracted (AVE)

Construct	Item	Skewness	Kurtosis	Item Reliability	Composite Reliability	AVE
Perceived Usefulness of Recommendations	PU1 PU2 PU3	-0.612 -0.213 -0.315[a]	0.287 -0.248 -0.356[a]	0.84 0.95 0.79	0.985	0.67
Trust	TR1 TR2 TR3	-0.547[a] -0.712 -0.215	0.210 0.784[a] 0.216	0.849 0.814 0.981	0.904	0.754
Reputation	RP1	-0.332	0.277	0.845	0.85	0.755
	RP2	-0.315[a]	0.242	0.799	0.72	0.731
	RP3	-0.321	0.224	0.819	0.76	0.743
Attitude	AT1 AT2	-0.557 -0.418[a] -0.384	-0.032 -0.051[a] 0.487	0.964 0.998 0.865	0.895	0.875
Intention	IN1 IN2	0.553 0.432[a]	0.488 0.241	0.811 0.985	0.871	0.854

[a] Significant deviation from normality.

Table 4: Discriminant Validity

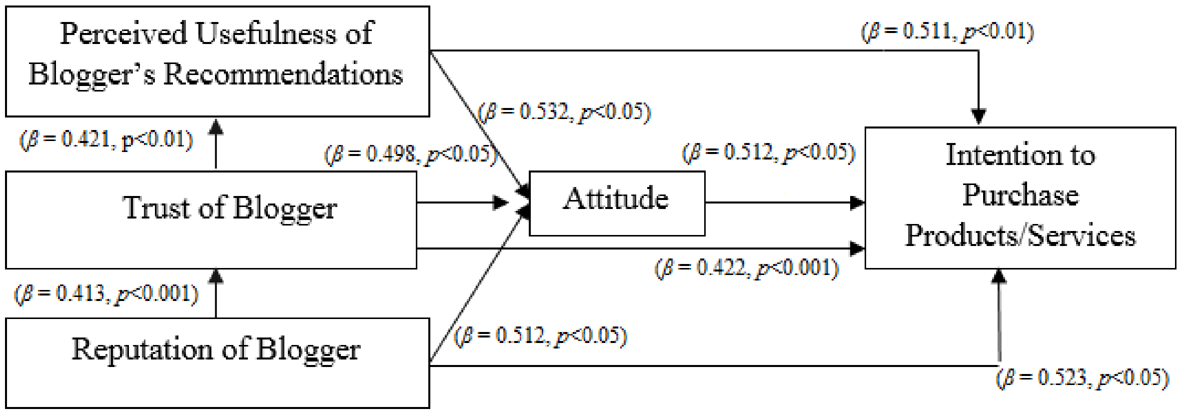
Items	PU	TR	RP	AT	IN
PU	1				
TR	0.215	1			
RP	0.321	0.021	1		
AT	0.023	0.755	0.033	1	
IN	0.031	0.023	0.378	0.845	1

Note: The diagonals represent the average variance extracted (AVE); the other matrix entries, the shared variance (the squared correlations).

D. Structural Model

The study has analyzed the structural model by testing the hypothesized relationships among various constructs, as illustrated in Figure 2 .The results showed that all of the hypotheses were supported. As expected, perceived usefulness of recommendations significantly influences attitude (β = 0.532, p<0.05), thus supporting H1. Perceived usefulness of recommendations significantly influences intention to purchase (β = 0.511, p<0.01); therefore, H2 is also supported. Moreover, trust significantly affects perceived usefulness of recommendations (β = 0.421, p<0.01), attitude (β = 0.498, p<0.05) and intention (β = 0.422, p<0.001); these findings thus support H3, H4, and H5 respectively. In addition, reputation significantly affected trust of blogger (β = 0.413, p<0.001), attitude (β = 0.512, p<0.05) and intention (β = 0.523, p<0.05); hence, results support H6, H7, and H8. The effect of attitude on intention was significant, as shown by the path coefficient of 0.512 (p<0.05), supporting H9. The significance of the variables can be observed in Figure 2.

Figure 2: Results of SEM



E. Recommended Products

It is important for companies to know when it is best to use blog marketing strategy. Hence, to gain further insight into the effectiveness of blogger recommendations, the online questionnaire was also designed to ask several open-ended questions such as "What kind of recommendations for products/services do you usually read on blogs?" Table 5 lists the results of this query, showing that 43.2 percent of the respondents review recommendations for fashion, 35.0 percent for food, 11.1 percent for cosmetics, 4.10 percent for travel related services, 2.96 percent for accessories, and lowest for books and investments. The findings suggested that retail sellers of these products/services should heavily use blog marketing strategies to inform customers about their new products/services, attract more customers to increase sales, and remind customers to buy products/services from them and not their competitors.

Table 5: Product/Service Recommendations Read on Blogs

Items	No. of respondents	%
Food	154	35.0
Cosmetics	49	11.1
Accessories	13	2.96
Travel-Related Services	18	4.10
Fashion	190	43.2
Investments	9	2.05
Books	6	0.01

V. Discussion and Conclusion

A. Discussion

Understanding the effect of blogger recommendations on the purchase of products/services is important for researchers and practitioners. Based on the findings of this study, several implications are discussed. The findings confirmed those recommendations, which were observed in the existing literature and previous studies (Park and Farr, 2007). Indeed, having informative and recommending bloggers would positively impact a consumer's purchasing attitude and intention.

According to the report by my Yearbook report (Wegert, 2010), bloggers have significant influence, as 81 percent of people seek recommendations through a social site before shopping (Osman *et al*., 2009). Consumers are not the only ones affected by appreciating the impressive shopping posts - bloggers have become persuasive individuals and opinion leaders for people around the world. People can acquire information and relevant knowledge about products/services as well as follow trends in shopping and places to visit. Bloggers are becoming a benchmark for the public in determining whether products/services are worthy to be adopted or not. Hence, this study verifies that consumers depend on blogger recommendations before making the final purchase decision (Corporate Eye, 2010).

Numerous studies have presented how consumers seek out reviews about the choices of products/services and believe that blogger recommendations may be significant at various stages of the consumer buying process (Jermyn, 2016; Scaraboto and Fischer, 2013; Hsu *et al*., 2013). Conceptually, the consumer buying process includes five stages: 1- need recognition, 2- information search, 3- evaluation of alternatives, 4- purchase, and 5- post-purchase behavior. The recommendations of bloggers may influence several stages of the consumer buying process. For instance, in the stage of need recognition, the content of the blogger recommendations is considered an external stimulus that may attract blog readers. Moreover, in the stage of information search, blogger recommendations are considered as a valuable source of information by many people. Similarly, recommendations written by bloggers may have a significant influence on the consumer's evoked set (consideration list of choices), thus influencing final purchase decisions. Finally, in the stage of post-purchase behavior, consumers may express their feelings after purchasing and using the product/service through the blog page. Therefore, the influences of blogger recommendations are multifaceted.

In addition to showing how blogger recommendations influence consumer attitudes and intentions to purchase products/services, the study has also found that trust and reputation of bloggers significantly and directly influences attitudes and intentions to purchase. The result seems consistent with previous studies by Hsu *et al.* (2013), Chu and Kamal (2008), and Lee *et al*. (2011), who verified that trust and reputation had an influence on consumers' purchase intentions to shop online. Consequently, it implies that consumers tend to accept recommendations by bloggers with high trust and reputation;, and thereby it develops positive attitudes and behavioral intentions for online shopping. The results highlight the importance of trust and reputation of bloggers. Moreover, the study confirms the direct influence of the perceived usefulness of blogger recommendation on purchaser attitudes and intentions. It means that blog readers would purchase products/services if they perceive the blogger recommendations to be useful (e.g., usefulness in terms of describing details of the product/service from blogger's self-usage experience, listing clear advantages and disadvantages of the product/service, discussing other alternatives similar to the product/service features, etc.).

B. Contribution of the Study

In terms of theoretical contributions, the study has contributed to the growing body of literature on consumer behavior and blogging. Particularly, it has shed much-needed light on the influence of blogger recommendations in consumer purchase decisions. This study replicates a previous study conducted on Taiwanese blog readers to understand the effects of blog recommendations on consumer purchase decisions. Moreover, this study extends the previous studies by adding a reputation factor to the model.

In terms of practical contributions, the results have valuable implications for retail sellers and business owners who wish to promote their products/services and increase sales. Based on the results of this study, perceived usefulness of blogger recommendations, trust, and reputation have been empirically confirmed as having significant influential effects on blog readers' attitudes and intentions to purchase products/services. Therefore, blogger recommendations seem to be a promising marketing strategy for increasing sales. Hence, marketers should utilize blogs, weblogs, and social media tools such as Instagram to help them positively influence consumer attitudes and intentions to purchase products/services. Experienced bloggers and opinion leaders are important because they help marketers to recommend and offer their products/services, stimulate customers to purchase, engage with customers, and build relationships with customers. Through blogger marketing activities, marketers can accelerate marketing efforts to influence consumers' purchasing attitudes and behavioral intentions. Moreover, marketers should expand their customer base by providing incentives and promotions for other customers through blogger posts. Lastly, the study found that positive attitudes and intentions to purchase products/services are shaped by blogger recommendations generated by highly reputable, trustworthy, and useful blogs. Hence, marketers should consider these factors when adopting bloggers in their marketing strategies to get effective outcomes.

VI. Limitations and Future Research

Like any other research, this study is not free of limitations. The results should be interpreted and accepted with caution for the following reasons. First, the main limitation is the choice of the sample as it was drawn only from undergraduate and postgraduate students in various colleges and universities in Kuwait, even though the results offer valuable insights and better understanding of the importance of blogger recommendations in consumer purchasing decisions. Precautions should be taken when generalizing these results to other settings and contexts because the respondents were relatively young and educated. However, the results can still provide better understanding of the effects of blogger recommendations and are intended to be used as a starting point to test those relationships in other contexts. Moreover, the subjects were blog readers in Kuwait. Culture, norms, traditions, and lifestyle may differ among people from different countries. Previous studies indicate that culture will impact IT usage (Leidner and Kayworth, 2006). Therefore, proper care should be taken into account when generalizing the results.

Future research is needed to further replicate the study by investigating the possible differences among various demographic factors. Such factors mainly include age, education levels, income levels, and different cultures. Other considerations may influence blog readers' attitudes toward purchasing products/services, such as education of blogger, attractiveness of blogger, perceived enjoyment of blogger, and negative blogger recommendations ("electronic word of mouth" or "eWOM"). It may be important to study how negative eWOM affects a blog reader's purchasing behavior, potentially leading to a variety of unexpected but useful results for marketers.

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Social Data Predictive Power Comparison Across Information Channels and User Groups: Evidence from the Bitcoin Market

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In the context of Bitcoin, we examine the relationship between Bitcoin price movement and social data sentiment. Baseline findings reveal that social media provides value-relevant information in both short-term and long-term predictions. By comparing the predictive power across different information channels and different user groups, we found that (1) while speculative information predicts both long-term and short-term returns effectively, fundamental-related information only predicts long-term returns, and that (2) prediction accuracy is higher for less active users than for active users on social media, especially in long-term prediction.

Keywords: Social Media, Digital Currency, User-Generated Content, Text Mining

JEL Classification: M15, G17

I. Introduction

Early during the last decade, people started to realize that the Internet was playing an increasingly important role in the financial markets (Tumarkin and Whitelaw, 2001). Besides traditional information sources such as earnings releases, financial analyst recommendations, and news services, technology advancement makes other means of information sources available. Today, social media has become an important outlet of value-relevant information and a new way to assist investment decisions.

Many practitioners embraced this method and achieved huge success. For example, Kensho, a large-scale data processing platform similar to Google search, focusing on answering real-time investment related queries, posets threats to financial analyst professionals. Datasift, a US-based company offering a powerful cloud platform to extract value from social media and make predictions, is currently worth more than a billion dollars. Cayman Atlantic, a hedge fund that invests based on sentiment analysis of Twitter and other media, achieved a cumulative annual return of 25.10% during 2014[1] and 10.42% during 2015[2]. Many other companies from different industries such as Goldman Sachs, Thomson Reuter's Eikon, IBM, and Bloomberg have also started to offer services based on social media sentiment analysis.

This phenomenon is landscape-shifting in the finance industry and has attracted attention from researchers. There is already abundant literature on the impact of traditional news media on stock prices (Davis *et al.*, 2012; Loughran and McDonald, 2011; Tetlock, 2007; Tetlock *et al*,.

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[1] For detailed information about the cumulative returns, please refer to Cayman Atlantic (2014).

[2] For detailed information about the cumulative returns, please refer to Cayman Atlantic (2015).

2008), and researchers are catching up with this trend to study the informativeness of social media for the financial markets (Antweiler and Frank, 2004; Chen *et al.*, 2014; Das and Chen, 2007; Tumarkin and Whitelaw, 2001). Several major online communities have been investigated, such as the Yahoo! Finance message board, RagingBulls and Seeking Alpha, etc.

In this research, we follow this line of investigation to answer two related questions: (1) Does the social media wear-in time differ across social media information channels? and (2) Is the prediction accuracy related to social media users' level of activity. To preview our results, we found that speculation-related information predicts both long-term and short-term returns, while fundamental-related information only predicts long-term returns. By comparing different user groups, we found that more accurate information comes from inactive users rather than active users.

Our research context is an emerging digital currency, usually known as cryptocurrency. It is a decentralized peer-to-peer electronic payment network. Though our research background is limited to the Bitcoin market, the insights can be readily generalized to other markets satisfying the following two conditions: (1) There must be a market to enable free trading of the underlying assets, and (2) There must be a social media to enable communications between peer investors. In recent years, social media have become an important unofficial information outlet due to their rapid development. With this trend, we believe that our paper will potentially shed light on trading behavior in an increasing number of domains in the years to come.

The rest of the paper is organized as follows. Section II reviews the related literature and develops our hypotheses. Section III describes our data and empirical analyses. Section IV concludes.

II. Literature Review and Hypothesis Development

Why do loosely organized social media play a role in the financial markets where the trading involving millions of dollars is conducted every day? It has already been noticed earlier in the finance literature that stock market participation increases with social interaction due to the word-of-mouth effect or observational learning (Hong *et al.*, 2004). However, to predict market price movements with social media, we have to answer two key questions.

First, why are people willing to share quality information with others? There are several reasons. First, people derive utility from attention and recognition from posting quality information that is subsequently confirmed by price movements. Second, message board viewers' reading and trading can have a price impact and expedite the convergence of market prices to what the authors perceived to be fair. Therefore, informed actors have the incentive to publicize their investment ideas (Chen *et al.*, 2014). Third, it has been shown that people contribute their knowledge when they perceive an enhancement of their reputation, and they contribute without expectations of reciprocity from others or high commitment to the network (McLure-Wasko and Faraj, 2005). The latent benefit of a social exchange process can be emotional comforts or social rewards such as approval, status, and respect (Shi *et al.*, 2014).

Second, why do people trust information on social media, where there is no guarantee of the information's quality? Several mechanisms have been identified in the related literature. Social media user-generated content (UGC) can potentially affect stock prices in the following ways (Tumarkin and Whitelaw, 2001): (1) posting activities may help predict stock returns if the message contains new information; (2) even if messages do not contain new information, they may also provide a better indication of general market sentiment than is already contained in the trading records; (3) even without any value-relevant information, investors may follow the buy and sell recommendations of message board users; and (4) traders may recognize the momentum generated by investors who follow message boards, thus exaggerating this effect. The existence of persuasion bias in social media also serves as an explanation (DeMarzo *et al.,* 2001). People fail to adjust properly for possible repetition of the information they receive, so when an individual in a social network hears a piece of information over and over again from peers, he or she will be further influenced.

In the related literature, some researchers attempt to predict short-term stock returns (Antweiler and Frank, 2004; Das and Chen, 2007; Dougal *et al.,* 2012; Solomon, 2012; Tetlock, 2007; Tumarkin and Whitelaw, 2001; Wysocki, 1998), while others predict long-term stock returns (Chen *et al.,* 2014; Davis *et al.,* 2012; Dewally, 2003; Womack, 1996). However, when we use social media analytics to predict market price movements, it is crucial to know approximately how long it takes for the information to be factored into the price (the "wear-in" time). A recent related study compared the wear-in time and predictive value of different information outlets and found that social media have higher predictive value and shorter wear-in time (Luo *et al.,* 2013). Still little is known about whether or not the wear-in time depends on the type of the information. In this study, we are on a mission to answer this question. Specifically, we compare two types of information: fundamental-related information and speculative information.

Fundamental-related information unveils inherent value and predicts future trends. But for a volatile market such as the Bitcoin market, it is unlikely that fundamental-related information is value-relevant in the short term because there are many market surprises constantly affecting the short-term Bitcoin returns since the Bitcoin market is still in an early stage. Examples include unexpected technical advancements, shocks, and security concerns, among other issues. Under such circumstances, even if the long-term implications embedded in the social data are correct, people are reluctant to trust and take actions immediately due to unexpected shocks and hyper risks. And to make things worse, traditionally people place less emphasis on social media outlets compared to financial analysts (Chen *et al.,* 2014). So we expect fundamental-related information to have a very limited short-term impact. However, if the prediction of the long-term trend is accurate, no matter whether people trust it or not initially, the future price movement will ultimately confirm the original social media predictions. As a result, we expect that fundamental-related information predicts, if it can, only the long-term Bitcoin price changes.

Now take a look at the speculative information. Speculation is defined as a process for transferring price risks (Tirole, 1982). It is the practice of engaging in financial transactions in an attempt to profit from fluctuations in the market value of a tradable good, rather than trying to profit from the underlying financial attributes. There is no determinate result in the finance literature as to whether or not speculation occurs in the short or long term. Both cases exist. So we expect that speculative information affects both short-term and long-term price movements.

In light of these considerations, we propose our first hypothesis:

Hypothesis 1: Fundamental-related information only predicts long-term price movements, while speculative information predicts both long-term and short-term price movements.

Next, we compare the predictive power of different user groups on social media. In recent years, searching for efficient ways to locate influential social media participants and to take advantage of them in marketing and advertising has attracted attention from many practitioners and researchers. Social media users differ in their activity level and their informativeness.

Understanding who keeps the social network attractive and who influences the activity of others is vital (Trusov *et al.,* 2009). In the related literature, influential people are believed to have three attributes: (1) they are convincing, (2) they know a lot (i.e., are experts), and (3) they have a large number of social ties (Goldenberg *et al.,* 2009). Most researchers focused on the third point. They are interested in influential people who can create buzz. However, very little attention is directed to those people who actually have accurate insights. Those people do not necessarily overlap with those who have a lot of social ties or those who are active on social media. In this paper, we compare the prediction accuracy of active users with high levels of activity to the prediction accuracy of inactive users with less presence on social media.

According to the literature review at the beginning of Section II, the motivations to share on social media are multifold, including latent emotional benefits (enjoyment of helping, reciprocal relationships), reputation enhancement, and expedited price convergence. Active social media users who regularly engage in communications are well rewarded with emotional benefits. However, for those who are very inactive, emotional benefits are not the main purpose; therefore, they must be motivated by other incentives such as reputation enhancement (McLure-Wasko and Faraj, 2005), and expedited price convergence. Intuitively, inactive social media users usually do not talk online for the sake of talk. If they share information with others, most probably they want to make a point.

In light of these considerations, we propose our second hypothesis:

Hypothesis 2: Inactive social media participants provide more insightful information than active social media participants do.

Almost all related studies are conducted using stock market data. We try to summarize the expected differences in the two settings. First, we expect better identification from the Bitcoin market. In the stock market, there are many confounding effects outside the social media such as periodic financial statements, firm announcements, and opinions from professional financial analysts. Some of the influences are difficult to control properly. Without the above-mentioned confounding factors, the Bitcoin market offers a much cleaner research background. Although there are editorial media outlets from major new services such as *The Wall Street Journal* news wires, we are able to control them in our paper using textual analysis. Second, we expect stronger effects from social media in the Bitcoin market because investors have to rely heavily on social media to obtain new information about Bitcoin in the absence of adequate official information sources. This prediction is supported by the comparison between coefficients estimates of our paper and those of a comparable stock market paper mentioned in the result section.

III. Data and Methods

A. Bitcoin and Bitcoin Return

Bitcoin, a type of digital currency (also known as cryptographic currency) launched early in 2009, has been increasingly recognized in recent years. The Bitcoin market capitalization shots up to over 10 billion US$ during 2016[3]. Though at a first look this technology resembles the credit card payment system, there are fundamental differences: (1) cryptocurrency platforms are running

[3] For detailed Bitcoin market capitalization data over time, please refer to the following link: https://blockchain.info/charts/market-cap.

on specialized currency, and the exchange rates with fiat currencies are decided at the exchanges, and (2) there is no central authority maintaining the operations, regulating the issuance of the currency, or keeping detailed records of every transaction.

Cryptocurrencies are also different from other types of virtual currencies (such as e-cash, DGC, prepaid card, etc.) in that its existence does not depend on any issuing institution, nor is it backed by precious metal. Its existence is based on cryptographic algorithms and a formula stipulating the growth of currency supplies outstanding. The motivations of building such a system are multifold, for example: (1) less dispute cost due to irreversible transactions; (2) no user identity theft and enhanced security; (3) global accessibility since transactions between payers and payees are not geographically limited; (4) money goes to payee’s account almost instantly; (5) controlled inflation; (6) the amount of money transacted and the transaction frequencies are not limited by a third party, and (7) anonymity and untraceable transactions.

The cryptocurrency industry has had substantial impacts on both the global currency system and the electronic payment system. Since it is still in its infancy, research on this topic has just begun. Most researchers approach this topic from a technical aspect. Many such studies discuss issues in the Bitcoin mining process (Eyal and Sirer, 2014; Johnson *et al.*, 2014; Miller *et al.*, 2015; O'Dwyer and Malone, 2013), and some examine other technical issues such as anonymity in the Bitcoin system (Reid and Harrigan 2013). However, studies from the perspectives of economics and finance are limited. A recent study investigates whether users’ interest in digital currency is based on its appeal as a currency or as an asset, and found that uninformed users adopt Bitcoin mainly as a speculation tool (Glaser *et al.*, 2014). An earlier 2013 study echoed the point of view that Bitcoin cannot be treated as currency due to its high volatility and hyper risks (Yermack, 2013). Though cryptocurrency has drawn some attention, there are many more issues to be addressed.

The baseline of this study is to predict Bitcoin price movements using related social data sentiments. We calculate the returns of Bitcoin using the exchange rate between Bitcoin and US$. The data period is from May 17, 2011 to October 28, 2014. To track the Bitcoin price movements, we collect Bitcoin price data from Bitstamp, a major “foreign exchange” between Bitcoin and many other fiat currencies. Similar to foreign exchange markets, the Bitcoin market is open 24 hours a day, and seven days a week. The Bitcoin prices used in the analyses are the 24:00 o'clock price on each day (the daily close price). All time stamps are based on GMT. The day t Bitcoin return is calculated as $(P_t - P_{t-1})/P_{t-1}$.

The Bitcoin market has been very volatile, especially during its earlier years. At the time of this study, the entire Bitcoin system is still immature: constant revolutions, disasters, and new government regulations frequently surprise the Bitcoin market. Over the entire data period, the highest daily return reached 41.38%, and most dramatic declines bottomed at -50.31%. But from the point view of model identification, this instability is advantageous since more variations are embedded in our data.

B. Social Media

We downloaded social media discussions from Bitcointalk.org, which is a very popular online message board about cryptocurrencies. There are many discussion sections on this website. However, most of them are either off-topic or only distantly related to Bitcoin valuations. Though there is a comprehensive discussion section called “Bitcoin Discussion,” which contains Bitcoin general discussions, we cannot effectively separate information into different categories. Since one of our intentions in this paper is to compare the "wear-in" time between different types of information, we only collect social data from specialized discussion sections. In particular, we employed a python script to download message board discussions from three sections: Speculative (Speculation about the Bitcoin price), Economics (Bitcoin from economics point of view, inflation/deflation, exchanges, Bitcoin loans etc.), and Trading Discussion (discussions about doing business with Bitcoin, best trading practices, delivery methods etc.). Examples of discussion topics in the three sections are provided in Table 1 (the exact words from bitcointalk.org).

To measure the sentiment of the social media discussions, we follow the literature and use the percentage of negative words. The negative word list we use is constructed by Loughran and McDonald (Loughran and McDonald 2011), which is a word list modified from the Harvard Psychosociological Dictionary (2017) to fit into the financial contexts. The sentiment expressed by all discussions during a certain day is the average percentage of negative words for all postings and replies of that day (Chen *et al.* 2014). In this way, we calculate our three key sentiment variables $Speculation_t$, $Economics_t$, *and* $TradingDiscussion_t$ respectively.

Besides social media, traditional media are also important sources of information. To control their impact, we downloaded Bitcoin-related editorial news articles from FACTIVA. Specifically, we searched on FACTIVA with keyword "Bitcoin", and limited our attention to articles written in English and published in major newswires (*The Wall Street Journal*, Dow Jones news wire, and Reuters news wire). We ended up with 13,216 articles. The earliest article about Bitcoin on FACTIVA was published on May 17, 2011, the day on which our data collection starts.

Table 1：Discussion Topic Examples

Discussion Sections	Examples
Economics	Do you think Bitcoin will replace dollar soon? Will Bitcoin cause the end of public debt? Bitcoin or gold? What would you pick?
Speculation	Is this the next big run-up in price? 320$, what the hell is going on? Will BTC reach $350 during November?
Trading Discussions	Bitcoin arbitrage on Github: ~2% monthly return, market neutral long/short Selling Rate of BTC on Circle Higher Than Coinbase Best way for cashing in

C. Traditional Media Controls

To measure the information contents of the traditional media, we put together all articles published on the same day and applied textual analysis (calculating the percentage of negative words). Similarly, we used the negative word list constructed by Loughran. All time stamps in this paper are based on GMT. The descriptive statistics are shown in Table 2.

Table 2: Descriptive Statistics

	Economics	**Speculation**	**Trading Discussion**	**Traditional Media**
Total # Observations	1261	1261	1261	1261
Total # Articles	106,031	277,329	56,836	13,216
Avg. % Negative Words	1.52	1.30	1.16	1.61
StDev % Negative Words	0.62	0.58	0.72	0.77
Max % Negative Words	8.26	6.88	10.15	6.28
Min % Negative Words	0	0	0	0

D. Main Results

We organize our main analysis around the following baseline regression specification:

$$R_t=\alpha+\beta_1 Economics_t+\beta_2 Speculation_t+\beta_3 TradingDiscussion_t+X\delta+\varepsilon_t$$

This regression tests the baseline expectation in this paper. First, we examine the effects of social media discussions on the end-of-day price movements. Since Bitcoin is traded 24/7, the intraday return is calculated using the 0:00 price and 24:00 price of day *t*.

Our key independent variables are the average fractions of negative words in the three discussion sections: $Economics_t$, $Speculation_t$ and $TradingDiscussion_t$. If social media does help predict the end-of-day Bitcoin price movement, the coefficient estimates for the three sentiment measures should be negative. *X* includes our control variables: $TraditionalMedia_t$, $Volatility_t$, R_{t-1}, and R_{t-2}. Volatility_t is calculated as the sum of squared daily returns during the previous calendar month.

Table 3 presents the result for the end-of-day price movement predictions. In Column (3), the coefficient estimates of $Speculation_t$ and $TradingDiscussion_t$ are -1.292 and -1.651 respectively, implying that the end-of-day price will be 129% (165%) lower when there are 1% more negative words in the Speculation (Trading Discussion) sections during that day. However, there are no significant results for $Economics_t$.

Table 3: Predict End-of-Day Price Change with Social Media

	(1)	(2)	(3)	(4)
$Economics_t$	-0.271 (-0.77)	-0.218 (-0.62)	-0.249 (-0.71)	-0.531 (-0.93)
$Speculation_t$	-0.812** (-2.27)	-0.775** (-2.17)	-0.747** (-2.09)	-1.292** (-2.26)
$TradingDiscussion_t$	-0.950*** (-3.12)	-0.939*** (-3.09)	-0.951*** (-3.13)	-1.651*** (-3.83)
R_{t-1}		0.077*** (2.74)	0.075*** (2.67)	0.098*** (2.79)
R_{t-2}		-0.057** (-2.05)	-0.059** (-2.11)	-0.039 (-1.12)
$Volatility_t$			0.013 (1.28)	0.025* (1.95)
$TraditionalMedia_t$				0.341 (1.10)

***=P<0.01, **=P<0.0 5, *=P<0.1.

This response may appear to be unrealistically large at first, but since the average fraction of negative words is around 1%, a 1% increase is rather significant. Also, the Bitcoin market is characterized by huge price volatility. This method of payment is not yet widely accepted in transaction partly due to the volatility problem. The US$ equivalence of 1 Bitcoin was only $0.30 in January 2011 but this number skyrocketed to $1,300 during November 2013. The sharpest one-day drop occurred on April 11, 2013 when the price fell from over $260 to $77.56.

Also, due to limited information sources within the Bitcoin market and the absence of institutional investors, social media are a major information source, and have significantly amplified effects on the price. Considering all the factors above, we expected a significant difference in the scales of the results from similar studies in the stock market. The results in Chen *et al*'s (2014) paper show a 0.25% to 0.28% drop in returns when the fraction of negative words in Seeking Alpha articles increases by 1%, which is a much smaller impact.

Many related studies on the stock market are focused on the prediction of the next-day price movements and obtain significant results. We also tested the predictive power of social media for the next-day price change. The results are presented in Table 4. Notice that the coefficient estimates for variables $Speculation_t$ and $TradingDiscussion_t$ are no longer significant. Evidence shows that social data only predicts the end-of-day price movement within the context of Bitcoin, but not the next-day return. This is different from the cases in the stock market. The reason lies in the differences in the structure between the stock market and the Bitcoin market.

Like all other cryptocurrencies, Bitcoin is traded 24/7, therefore if the market is efficient, any information that is valuable in the short term will factor into the price by the end of that day. As a result, the Bitcoin returns calculated using 0:00 price and 24:00 price only reflect price changes within the current day but not the next day. However, in the stock market, there are market closures. Any relevant information released after the market closure will only possibly affect the next-day return (returns in the stock market are usually calculated using closing prices of two successive days).

Table 4: Predict Next-Day Return with Social Media

	(1)	(2)	(3)	(4)
$Economics_t$	0.079 (0.22)	0.069 (0.20)	0.037 (0.11)	-0.202 (-0.34)
$Speculation_t$	0.009 (0.02)	-0.040 (-0.11)	-0.012 (-0.03)	-0.272 (-0.46)
$TradingDiscussion_t$	-0.102 (-0.33)	-0.085 (-0.28)	-0.098 (-0.32)	-0.039 (-0.09)
R_{t-1}		-0.052* (-1.85)	-0.054* (-1.92)	-0.035 (-0.97)
R_{t-2}		-0.026 (-0.91)	-0.027 (-0.97)	-0.066 (-1.85)
$Volatility_t$			0.013 (1.28)	0.014 (1.09)
$TraditionalMedia_t$				0.403 (1.27)

***=P<0.01, **=P<0.0 5, *=P<0.1.

Following the baseline results, we test our Hypothesis 1 next. As mentioned in the introduction, some researchers predict short-term returns but others predict long-term returns, and lately, they have begun to investigate the "wear-in" time of different social media metrics (Tirunillai and Tellis, 2011) and the "wear-in" time of different information channels (Luo *et al.*, 2013). In this article, we follow this line of investigation to test if the wear-in time depends on the type of information.

Examples in Table 1 suggest that people are more interested in the inherent value, and the future trend of Bitcoin in Economics related topics, but are more concerned about the price change and predictions in Speculation and Trading related topics. We thus compare the predictive power of two different types of information: fundamental-related information and speculative information. Fundamental-related information is measured by $Economics_t$, and speculative information is measured by $Speculation_t$ and $TradingDiscussion_t$. Our Hypothesis 1 posits that the fundamental-related information predicts long-term price changes, while in contrast, speculative information predicts both long-term and short-term price changes.

A similar model is used in this section except that the dependent variable is now the cumulative returns ($R_{t,t+a}$). We use the social media discussions observed at time t to predict the cumulative returns from t to $t+a$. We empirically examine the predictive power for one-week, one-month, and three-month cumulative returns respectively. The result is shown in Table 5.

The first column in Table 5 is the same as the previous result in Table 3. We include it here just for comparison. Column 1 of Table 5 shows that Economics related discussions do not predict short-term returns, and this is also true for one-week and one-month cumulative return predictions. However, in the last column in Table 5, the results demonstrate a strong predictive power for the three-month cumulative returns. The coefficient estimate jumps from below 1 to a very high value. For the speculative information, represented by $Speculation_t$ and $TradingDiscussion_t$, we only detect predictive powers for short-term price movements, basically within one week (columns 1 and 2 of Table 5).

Table 5: Fundamental-Related Information vs. Speculative Information

	R_t	$R_{t,t+7}$	$R_{t,t+30}$	$R_{t,t+90}$
$Economics_t$	-0.531 (-0.93)	-0.932 (-0.58)	-0.242 (-0.04)	-50.636*** (-3.11)
$Speculation_t$	-1.292** (-2.26)	-4.096** (-2.56)	-2.535 (-0.41)	-25.133 (-1.54)
$TradingDiscussions_t$	-1.651*** (-3.83)	-2.361* (-1.95)	-0.696 (-0.15)	-5.672 (-0.46)
R_{t-1}	0.098*** (2.79)	1.304*** (13.19)	0.719* (1.86)	0.814 (0.81)
R_{t-1}	-0.039 (-1.12)	1.152*** (11.88)	0.643* (1.69)	1.247 (1.26)
$Volatility_t$	0.025* (1.95)	0.151*** (4.25)	-0.499 (-3.59)	-2.882*** (-7.98)
$TraditionalMedia_t$	0.341 (1.10)	-0.848 (-0.98)	-7.042** (-2.08)	-10.244 (-1.16)

***=P<0.01, **=P<0.0 5, *=P<0.1.

Next, we investigate if the information provided by different user groups on social media platforms differs in informativeness for future price movements. As mentioned before, influential people on social media usually possess three attributes: (1) they are convincing; (2) they are experts, and (3) they have a lot of social ties. In this paper, we focus on the second point. What kind of social media users provide accurate information? This is the question we try to answer to test our Hypothesis 2.

On Bitcointalk.org, there are several user badges. From high to low in terms of activity level, they are: Legendary, Hero Member, Senior Member, Full Member, Member, Junior Member Newbie and Brand New. The activity score is calculated based on activity levels on Bitcointalk.org and the time since registration, specifically, Activity = min (time×14, total # posts), which means that high-level users are those who are active on this message board for a long enough time. We define two user groups: the active user group (Legendary, Hero Member, Senior Member, and Full Member level users) and the inactive user group (Member, Junior Member, Newbie and Brand New level users). We calculate the social media sentiments for topics initiated by active users and inactive users respectively and then redo Table 5 for each user group. The results are shown in Table 6.

We observe dramatic differences between active and inactive users in terms of predictive power in Table 6. Panel A reports the results for active users, and Panel B reports the results for inactive users. For discussions under the Economics category, active users do not predict returns for any of the four holding periods (first row of Panel A). However, in Table 5, Economics related discussions by all social media participants combined demonstrate predictive power for the long-term returns (three-month cumulative return). Therefore, this predictive power has to come from the inactive users. And this is indeed the case as shown in the Panel B of Table 6. The first row in Panel B evidences the predictive power of the Economics related topics for the inactive users. As we expected, $Economics_t$, the sentiment of the fundamental-related information, does not provide much valuable information for short-term price movements, but successfully predicts the long-term returns, and the coefficient estimates are almost three times larger than they are in Table 5.

Table 6: Comparison Between Active and Inactive Users

	R_t	$R_{t,t+7}$	$R_{t,t+30}$	$R_{t,t+90}$
Panel A: Active User				
$Economics_t$	-0.816 (-1.41)	-0.665 (-0.41)	5.503 (0.88)	-22.514 (-1.43)
$Speculation_t$	-1.086 (-1.89)	-3.105* (-1.93)	3.649 (0.58)	-2.63 (-0.17)
$TradingDiscussion_t$	-1.795*** (-3.37)	-3.600** (-2.42)	4.457 (0.77)	5.666 (0.39)
Panel B: Inactive User				
$Economics_t$	-1.253 (-1.48)	-4.616* (-1.95)	-17.171** (-1.92)	-153.180*** (-6.62)
$Speculation_t$	-2.465** (-2.32)	-9.281*** (-3.12)	-33.282*** (-2.87)	-109.933*** (-3.78)
$TradingDiscussion_t$	-1.624*** (-2.84)	-0.618 (-0.39)	-11.046* (-1.78)	-32.639** (-2.09)

***=P<0.01, **=P<0.0 5, *=P<0.1.

For speculative information, the active user group shows predictive power only in the short-term (the second and third rows of Panel A). However, for the inactive users, the coefficient estimates are also significant for the one-month cumulative return prediction and the three-month cumulative return prediction (the second and third rows of Panel B). These results reveal that active participants are not necessarily informative on social media. The valuable information more likely comes from less active users because they share information with other not for emotional benefits (social comfort, maintaining reciprocal relationships, etc.), but to make a valid point. Even if those inactive social media participants do not post frequently, as long as the information or judgment is accurate, the price change in the future will ultimately confirm the value of the information.

To summarize, our analysis presented in Table 6 provides evidence that inactive users offer better predictions for future Bitcoin price movements, while the active users do not. The intuition behind this observation is that active users usually talk on social media for the sake of talk, while inactive users usually talk on social media to make a point. They have different motivations to share on social media which leads to differences in informativeness. However, active users still provide valuable information for short-term price movement, and the predictive power difference mainly shows up in the long run.

IV. Conclusion

The development of information technology has made available new sources of information to assist investments for retail investors. In this paper, we examined whether unregulated social media provide valuable information for short-term and long-term predictions of Bitcoin valuation. We found that it is possible for retail investors to identify value-relevant information via communications over social media. The main results in our research that add to the related literature are that fundamental-related information predicts only long-term returns, while speculative information predicts both long-term and short-term returns. Also, we found that active users on social media do not overlap with inactive users with accurate information. Information provided by inactive user exhibits stronger predictive power than that of active users, especially in long-term prediction.

With the rapid development and usage of social media, there is a huge amount of social data generated each day. Knowing who provides more accurate information is crucial. Our research provides guidelines for identifying useful information on social media. Our research also suggests ways to estimate the "wear-in" time of different types of information (speculative information and fundamental-related information). This is another important factor to consider when predicting future price movements with social data.

Lastly, we point out some limitations of the paper and propose future research opportunities to extend this paper. The dataset used in this paper is a time series dataset; though we can eliminate the time-invariant effects by controlling for the lagged price movements, it is hard to control the general trend over time. For future research, a panel data collected for multiple cryptocurrencies may solve the problem by adding time-fixed effects and cryptocurrency-fixed effects to the model.

A more challenging, but arguably more important question is the effect of real and fake news on the Bitcoin prices. Is it possible to distinguish the real news from the fake news? If so, will it affect the prices in a different way? Investors have limited capability to tell fake news items from real ones, especially in a market with limited access to official news outlets. As a result, the fake news may also have a significant impact on trading. It will be a breakthrough if we can potentially identify fake news in social data, and compare its effects to that of real news.

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When Are Crowdsourced Data Truthful, Accurate, and Representative?

By LIAM BRUNT AND ERIK MEIDELL[*]

We trace crowdsourcing, as a business strategy to gather information, to Britain in the Industrial Revolution, when it was used to create trade directories. We show that the trade directories' occupational snapshot was very highly correlated (≈0.99) with the 1851 census – a valuable objective metric of accuracy. Accuracy of modern crowdsourced data is more difficult to judge, but seems somewhat lower; we make an explicit comparison to Yelp. We rationalize our results by considering: construction of the sampling frame; incentives of the crowd to report correct information; disincentives to report incorrect information (cost of contributing, presence of "gatekeepers"); and sampling strategy.

Keywords: Crowdsourcing, Sampling, Census, Inference

JEL Classification: C81, C83, M55, N01

I. Introduction

Over the last decade, crowdsourcing has become a key strategy for gathering information. Online reviews of products and services present the most obvious example. Consumers can almost costlessly access firsthand information about any product that they want to buy. Typically, there are tens – and frequently hundreds or thousands – of customer reviews for virtually any product offered on Amazon, or the website of any major retailer. In fact, there are so many more reviews than anyone could feasibly read that they have to be aggregated into summary statistics: as well as star ratings, many websites provide average scores for durability, ease-of-use, value for money, and so on. While retailers offer reviews as a convenience for their customers – i.e., it is sideline to their main business – many websites now exist *only* based on crowdsourced information. An obvious example is TripAdvisor. Visitors check the site primarily to see other people's reviews of places that they themselves are considering visiting; TripAdvisor then makes money by selling advertising for associated products and services. The most extreme case is Wikipedia – a platform consisting entirely of crowdsourced content that makes no profit at all: it exists only to crowdsource.

But crowdsourcing is a key element in many other, less obvious, information collection mechanisms. For example, prediction markets essentially provide a platform for countless individuals to bet anonymously on the outcome of an event, such as the U.S. presidential election. The odds of each candidate winning are derived from these bets, and have proved remarkably accurate at forecasting the winner. In the prediction case, the crowd comes to the platform to share

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information. In other cases, the platform actively seeks information from the crowd, such as firms using software to search social media for user sentiment (Evans, 2016). Crowdsourcing is frequently used in China to track people down, such as hit-and-run drivers: someone puts out a blurry photo of a car or an individual on SinaWeibo (the Chinese equivalent of Twitter) and within hours the perpetrator is usually unmasked (Simpson, 2014). The U.S. tried a similar approach after the 2013 Boston Marathon bombings, although that effort was less successful and actually wasted police time by generating a number of false leads (Wadhwa, 2013).

Note that there is a key difference between crowdsourcing to unmask criminals and crowdsourcing for book reviews. In the case of a crime, there is unquestionably a *right answer*. However, when 10,000 people rate a book or a tourist destination, they are not placing the item on an objective scale: if a book is not to one's taste then it may not be liked, even if other readers (with different tastes) gave it five stars. Even with similar preferences, it is not clear that everyone's scale maps directly to the scale of others; one person may give four stars while another gives five stars. Economists refer to this phenomenon as the problem of comparing "interpersonal utility". So, the most that can be said in considering these reviews is that "many readers liked it". In contrast, a certain person is going to win the U.S. election, and certain perpetrators carried out the Boston bombing: there is a clear benchmark against which to judge the truthfulness and overall accuracy of information.

If we are to rely on crowdsourcing to gather business information, then we need to be sure that the information is truthful, accurate, and representative. We can make this assessment only if we have an external metric against which we can evaluate it. An important element of our setting is that we have a clear, objective measure against which we can judge the accuracy of our crowdsourced data. First, we examine the occupational structure of England in 1851, as revealed by trade directories and the U.K. Government census; second, we examine the business structure of Norway in 2017, as revealed by Yelp and Norwegian Government establishment data. When we survey the literature in the next section, we will see that it is almost unique to have such a metric. Our empirical analysis will show that crowdsourced trade directories are remarkably accurate, particularly the historical ones. This then raises the question as to why? We argue that the answer lies in the information structure – how the crowd was tapped for information, how many crowd members reported on each individual fact, and how incorrect information was excluded. The next section gives more detail on the important variations in information structure that we see in crowdsourcing.

II. Crowdsourcing: Approaches to Information Gathering and Assessments of Accuracy

Suppose we use crowdsourcing to collect information about a well-defined aspect of the world. How accurate is this crowdsourced information likely to be? What are the incentives for different people – for example, informed versus uninformed – to participate? Even if everyone is informed, will the respondents be randomly drawn from the population? Are lovers or haters more motivated to give feedback on a product or service? It is hardly an exaggeration to say that crowdsourced information is changing the world. In fact, this is at the heart of the current concern about "fake news" (BBC News, 2016): many people now get their news via links that are shared (typically sourced from a Twitter or Facebook crowd) rather than the mainstream media, where facts have historically been more carefully checked. Even governments have adopted crowdsourcing as a *modus operandi*. For example, the U.S. government set out plans for a prediction market for terrorist attacks in order to try to get advance warning (Yeh, 2006), and

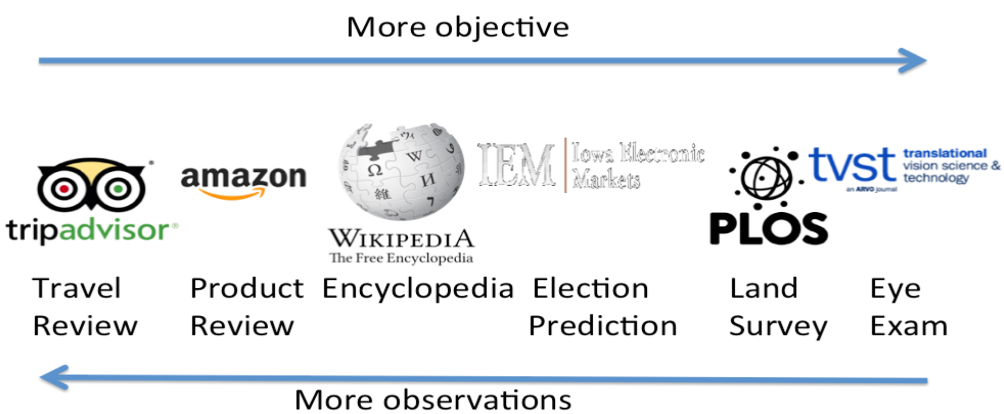
NOAA is testing software to take automated bathymetric readings from private vessels navigating U.S. waters (Reed, 2016).

There has been some discussion of the issues that we raise here (Surowiecki, 2004). But remarkably little research has examined the process of crowdsourcing, how it might be structured, and the accuracy of the output. The exception is Wikipedia, where several studies have sampled articles and given them to experts to have their accuracy assessed; they have sometimes been compared to matched articles drawn from established reference works, such as *Encyclopedia Britannica,* in which all the articles are supposedly written by experts (Giles, 2005). The accuracy of Wikipedia is generally considered to be good. However, Wikipedia is not a typical example of crowdsourced information. Note that each article is parsed by many people who collaborate to refine it (i.e., a large crowd is asked to agree on one item). This is analogous to Galton's original discovery – which he himself found surprising – that many people estimating the weight of an ox at an agricultural show together get very close to its true weight (i.e., the average estimate is accurate, even though the individual estimates vary widely; see Galton, 1907). But in many crowdsourcing contexts, *one* member of the crowd is asked to provide *one* piece of information – like a mosaic tile – and this is placed next to others to build a picture of the overall situation. The statistical properties of this approach are clearly very different: there is no averaging effect at work. Many examples of this exact situation are found in the geography literature, where researchers have tried to use the presence of the crowd "in the field" to report local mapping information (Al-Bakri and Fairbairn, 2010) or have used volunteers to categorize land use based on a mosaic of aerial photographs (See *et al.*, 2013; Salk *et al.*, 2016). Accuracy is generally low (only 62 percent of photographs were correctly categorized in the 2013 study, and the correlation of the crowd with a sub-set of expert evaluations was low in the 2016 study). Importantly, accuracy is also inferior to traditional methods (the OpenSourceMaps were significantly less accurate than the Ordnance Survey equivalent in the 2010 study). In our historical case from the British Industrial Revolution, we have a combination of formats: there is a mosaic effect, in that data are collected on businesses located in different towns; but there is also a kind of averaging effect, in that the business list for each town is parsed by multiple members of the crowd (so individual errors – in particular, omissions due to ignorance – may be eradicated as the crowd becomes larger).

Better crowdsourcing results have been reported in medical studies. For example, a volunteer crowd proved no worse than experts at detecting severe eye abnormalities from retinal scans (Mitry *et al.*, 2016), although the crowd performed substantially worse with cases of mild damage (around 60 percent, depending on which measure is used). Importantly, we are not told the accuracy of either group (crowd or expert) compared to the actual clinical condition of the patients (i.e., there is no truly objective measure used in the study). Better results have also been reported with prediction markets, although these conclusions have been challenged. In particular, it has been claimed that prediction markets are superior to traditional polling techniques in forecasting the outcomes of presidential elections (Berg *et al.*, 2008). But this is true only if we compare the forecasts throughout the election campaign; if we compare prediction markets and polls on the eve of the election, then polls are better. Why would you wish to disregard earlier information? Because voting intentions may change through the election campaign. Since we have no objective measure of voters' intentions *before the election date,* we cannot assume that the prediction markets were more accurate than the polls before the election date. It could be the case that the polls were correct – and the prediction markets incorrect – at the time the polls were taken. Notably, neither of them was very accurate in the 2016 U.S. presidential election. This takes us back to the general problem: assessing the accuracy of crowdsourcing requires an objective metric against which to compare it, and this is typically absent (as in the case of reviews) or prohibitively expensive to obtain (the output of the crowd may need to be somehow sampled by experts or a clinical analysis to gauge its accuracy). We overcome this problem in our study by comparing the crowdsourced data to the objective measure of the 1851 census, kindly prepared for us by the U.K. Government.

Some of these issues are summarized in Figure 1. We often have many observations of something that is not objectively verifiable (such as TripAdvisor telling us that a holiday destination is "five star"). There are also some instances where we have very few observations of something that is objectively verifiable (such as whether a photo displays symptoms of eye disease). But relying on very small numbers of observations – typically one – is not harnessing the power of the crowd: Galton's original insight was that averaging the crowd's estimates greatly increases accuracy, compared to relying on any single individual. Moreover, the settings in which the crowdsourced information is objectively verifiable have generally not effectively tested its accuracy against the available external metric (such as whether or not the patient really has eye disease). The only real test of crowdsourcing has been in the context of Wikipedia, where crowds have been used to parse every piece of information and where the facts can be checked against alternative information sources. The results for Wikipedia have been promising. But Wikipedia has another peculiarity of its information structure which we believe is crucial to its accuracy and which we will discuss in detail in the next section: "gatekeepers" (i.e., article editors) who can reject information that they know to be incorrect.

Figure 1: A Spectrum of Crowdsourcing Types



Finally, a natural assumption might be that effective crowdsourcing requires modern technology, such as the internet or mobile phones, because it reduces the cost of contributing. The historical account that we offer in this paper shows that such an assumption would be false. (Indeed, we will argue later that making it somewhat costly to contribute is a benefit because it discourages the contribution of incorrect information.) In the next section, we trace crowdsourcing back to the creation of trade directories in Britain in the 1790s, when people were working with paper and quill pens. We discuss how the crowd was tapped for information, and why this was likely to result in accurate data; we contrast this with government efforts to collect information. In the succeeding section, we compare the occupational structure represented in trade directories to "hard" information from the 1851 occupational census, and show that the data are highly correlated at the town level. Our final section draws out the key lessons from our story.

III. The Creation of Trade Directories

Samuel Lee prepared the first British trade directory in 1677, but the entries covered only 1,953 wholesale merchants living in London (Goss, 1932). It seems to have met with limited success, since the exercise was not repeated until Henry Kent produced a new directory in 1734. Kent followed the same format as Lee but included 693 fewer names – so either London had shrunk or Kent's directory was very incomplete, the latter seeming more plausible. Coverage seems to have improved over the first few editions (up to 2,006 entries in 1740), but Kent's ambitions remained very limited in his subsequent annual revisions. Osborn's London directory first appeared in 1740 and offered a wider range of information, but was seemingly still very incomplete. The bar was finally raised in 1763 with the appearance of Mortimer's *Universal Directory*. He included not only the merchants and bankers of London but also people in other trades and professions: artists, musicians, doctors, lawyers, booksellers, shopkeepers, and so on. By the early nineteenth century, the *Post Office London Directory*, which first appeared in 1800, contained around 11,000 entries; and Johnstone's 1817 directory was up to 27,000.

Importantly, Sketchley produced a directory for Birmingham in 1763 – the first for a town outside London (Norton, 1950). The first two editions of Sketchley's directory have not survived, but the third edition (1767) has a format very similar to Mortimer's *Universal Directory* for London. Directories soon appeared for many other towns around England and up to 50 new directories were produced between 1763 and 1790. These covered ten towns, and some also attempted to cover larger areas, with county directories appearing for Hampshire (1784) and Bedfordshire (1785). William Bailey, in 1784, was the first to attempt a national directory that covered the principal towns throughout the kingdom. Wilke's *Universal British Directory*, which appeared in eight volumes between 1791 and 1798, raised the bar again by including many smaller towns.

In the early nineteenth century, town and county directories became common. In total, Norton's exhaustive survey (1950) counts 878 provincial (i.e., non-London) directories published before 1856. Many of these directories are readily available in electronic format because they are of interest to genealogists; therefore, they constitute one of the most accessible historical sources. Over time, directories became more thorough and complete and were produced to a higher standard. Famous names – such as Pigot's and White's – started to appear in the 1810s; they set out to cover the whole country both systematically and repeatedly. Repetition is a key ingredient in generating a worthwhile data source. First, it may enable us to trace changes over time using a consistent source. Second, it probably generates a more accurate directory. How does repetition increase accuracy? First, the directory producer had an extra incentive to ensure that his directory was accurate because he had a reputation to maintain to generate future sales. Second, he had experience in producing directories and thereby a better idea of how to elicit accurate information (as we discuss further below). Third, the directory producer already had local knowledge when preparing his directory (i.e., the data base generated by the previous edition).

The issue of accuracy is, of course, crucial. First, consider what we mean by accuracy. It is obviously not the case that the entire population was listed in a trade directory. Poor people would not have been listed; nor would many better off people who were not involved in trade (for example, retired people or military officers or noblemen). In fact, it is highly unlikely that even all the traders were recorded. There may be systematic omissions – such as dung collectors, who might not have wanted to advertise their trade – as well as random omissions and errors. In that sense, the directories are incomplete. But this does not make the directories useless. If we want to track business development over time, or map variations across the country, then we do not necessarily need a complete register of all traders and producers. What we desire is transparency and, preferably, consistency. If we know the likely sources of error – so that we can correct them – or if we know that they remained constant over time, then we may be able to say something worthwhile about changes or variation in business structure.

So how did directory producers compile their data? Several approaches seem to have been adopted (Norton, 1950). Early producers, such as Bailey and Pye, claim to have visited every house in the locality to elicit information from the householder. Pye, in fact, states that he gave up this approach in his later directories because it was too expensive. It may also have been counterproductive because people knocking unexpectedly at the door and asking about the nature of the householder's business might be suspected of being tax collectors – and therefore lied to, or told to go away. In any case, personal interviews could not have been a practical mode of compiling county or national directories because the task was simply too vast for a private entrepreneur. Thus, it became common to use local agents to collect information. For his *Universal British Directory* – which remained the most ambitious directory undertaking for several decades – Wilkes first enlisted local printers and booksellers as his agents. This was a natural step, given that he must have had contacts in the publishing world; in a moment, we discuss the merits of this approach, in terms of information accuracy and completeness. Wilkes then crowdsourced in order to improve the quality of the directory further. A draft of the local directory was left with a prominent resident of the local town and people were invited to inspect and correct it. Of course, as well as being a way of collecting information, this was also a form of advertising: people would be aware that the directory was going to appear, and might even be more likely to buy it because they had had a hand in preparing it.

Wilkes' approach provided several incentives for agents to furnish accurate information. The local printers and booksellers that Wilkes recruited were remunerated in the form of offprints for local sale, so they had a stake in generating an accurate and complete product. Logically, the first thing that a potential purchaser would examine to gauge the quality of a national directory would be his own town: if the local entries were accurate and complete, then he might be willing to believe that the rest of the directory was of similarly high quality; if the local entries were no good, then it would be difficult for the local bookseller to persuade the customer that the other entries were better. Thus, each local bookseller was likely to be able to retail his free offprints of the national directory only if he did a good job of collecting the data in his own town. We can think of Wilkes and the booksellers as "frame makers": Wilkes constructed the sampling frame (in a statistical sense) by choosing which towns to include in the directory; and the booksellers created a basic framework for each town, which could then have layers of information added to it by the townsfolk.

Now consider the actions of the crowd. When the draft was opened for correction by the townsfolk, the traders and professional people had an obvious incentive to ensure that the information about them was accurate and up to date – just as they have an obvious incentive today to check their name in credit registries (such as Experian) to make sure that no erroneous record is driving away customers. Not only might appearing in the directory attract business from out of town, but one could also imagine that there was a certain cachet derived from being in the directory. The same tactic is used by *Who's Who in Academia* – they persistently write to academic staff and ask them to complete a form with biographical details in order that they appear accurately in the next edition (which they can then buy for a special discount, of course). Friends, family, and business associates would also have an incentive to ensure that each business was correctly recorded, since they might benefit from any additional income. One can think of this tactic as using the crowd to minimize Type I errors – that is, erroneously rejecting (or omitting) a correct piece of information. Then we have the local "prominent person", who acted like a Wikipedia editor. He would have had a fair idea of who was in business in his neighborhood and this would have discouraged people from adducing false information – such as crossing out the names of competing businessmen on the basis that they had "gone to Texas" when really, they had not; or else writing that they themselves were a "cotton manufacturer and banker", when they were only a cotton manufacturer, in order to make themselves look more reliable. It is worth noting that all businesses in this period were sole proprietorships or small partnerships because joint stock companies were outlawed: thus all businesses traded under a personal name and were not anonymous in the way that modern businesses are. One can think of this tactic as using gatekeepers to minimize Type II errors – that is, erroneously accepting an incorrect piece of information.

We can contrast Wilkes' data collection approach with that of the government. When the first British census was undertaken in 1801, the Overseers of the Poor were employed as enumerators. They obviously had the advantage of local knowledge (albeit disproportionately of the poorest households); and they had the disadvantage of unpopularity. Moreover, people were always concerned that the government was collecting information for tax purposes. Therefore, England did not take an agricultural census until 1866 – whereas it started in France in 1840, for example – and even then, it contained data only on inputs, such as land and animals; data on outputs began to be collected only in 1885. So, it seems plausible that some people, at least, avoided the census enumerators and gave them the least amount of information possible. In fact, the earliest population censuses were restricted almost entirely to questions on the number and sex of household members. The censuses additionally report numbers of people "chiefly engaged in agriculture", "manufactures", and "otherwise". But these data are essentially worthless. For one thing, the data were recorded at the level of the household, not the individual, which immediately raises the question of what the household head reported when there were multiple people working in different sectors. Since many household heads had multiple occupations themselves – such as agricultural worker and carter – it is not even obvious how they reported their own chief occupation, let alone those of their wives and children. The occupational data are better in 1841, but really become usable only in 1851 (as we discuss below). Using the Overseers of the Poor as enumerators also had the disadvantage that the agents were not well trained – hence there seems to have been some confusion about exactly who was to be recorded and how (Higgs, 2005). Moreover, they did not have particularly strong incentives to be thorough because no one was willing or able to check their fieldwork. Finally, the enumerators had to do all their work on one night of the year, so they were in a big rush compared to the crowd and you might imagine that their returns would be incomplete (for example, if no one answered the door) or inaccurate (if someone was vague about their occupation). In the later censuses, such as 1851, there was an effort made to recruit and train specialized census takers, as used in modern U.K. or the U.S. censuses.

So, by comparison to Wilkes' approach, the census actually uses fewer people (only the enumerators, not a broad body of citizenry); with a lower level of knowledge (being experts only on the poor, not on their own and their neighbors' businesses); and worse incentives for accuracy (having nothing to gain personally from increased rigor); contributing information on more units of observation (every household, not just every business); in a shorter amount of time (just one night, rather than over a period of time). It seems plausible that the census could even be less accurate than the trade directory under such conditions. In fact, this problem is still a hot topic in the U.S. (Sullivan, 2009). The U.S. Census Bureau would like to use sampling in certain areas to estimate the population because they believe that it is more accurate to survey some areas very intensively and then reflate the survey data than to ask their enumerators to try to make an actual count of everyone (including the homeless and illegal immigrants and others who actively avoid authority figures). The Republican Party opposes this move precisely because it would lead to higher estimates of the number of poor people, which would affect the costs of government relief programs and so on.

IV. Comparing Trade Directories to the Census

If we can establish the representativeness and the accuracy of trade directories, then we can establish the effectiveness of crowdsourcing. One line of attack is to examine how closely the occupational structure recorded in trade directories maps to the occupational structure reported in the census. Note that we are testing a joint hypothesis here: that the trade directories are both representative and accurate. Absence of a mapping may be due to *either* unrepresentativeness *or* inaccuracy (or both); if we find no correlation then we cannot be sure which part(s) of the hypothesis is (are) rejected. But if we reject the alternative hypothesis (i.e., that there is no correlation), then we can be sure that the two requirements (representativeness and accuracy) are both met.

Comparing trade directories to the census is difficult for several reasons. First, trade directories report the number of businesses operating in each occupation in each town, whereas the census reports the number of workers employed. We therefore need to divide the total number of people in each occupation by the average number of employees per business (in that occupation) to infer the number of businesses in each occupation. This generates a sort of national trade directory for Great Britain (albeit a trade directory with the street addresses and names of the businesses removed). Census data are broken down by county and by major town, which enables us to match the data to many town-level trade directories.

Second, the quality of the occupational data collected in the census was very poor up to 1841, so if there were a low correlation with the trade directories then we would not be able to tell whether this was due to the low quality of the directories or the low quality of the census. By contrast, the Registrar General devoted an enormous amount of effort to systematizing the collection of occupational data in 1851, and it really represents a high point in the collection of occupational data (i.e., the data became coarser in subsequent censuses). A huge amount of groundwork had been laid, in terms of preparing and categorizing a list of 1,089 occupations that covered all the major employments of the nation (British Government, *Census of Great Britain, 1851: Population Tables II,* vol. 1, lxix-ci). We therefore take 1851 as our benchmark date for comparison to the trade directories. This has the additional advantage that the 1851 census contains a table of employees per business (British Government, *Census of Great Britain, 1851: Population Tables II,* vol. 1, cclxxvi-cclxxix), broken down by occupation, which we need to convert the numbers of workers reported in the census into the number of businesses.

Of course, the procedure turns out to be more complicated than this. First, the 1851 table of employees per business enumerates only those businessmen ("Masters") who have more than zero employees ("Journeymen and Apprentices"). So, we must infer how many businessmen there were who had zero employees. In principle, this is straightforward because, for each occupation, the table reports the number of employers having a number of workers. If we were to multiply all the employers in an occupation by the number of workers that each of them employed, then we should get the total number of people working in that occupation *except those businessmen who employed* *zero*. We could then compare this number to the total number of people recorded in the census as having that occupation. Any difference should (in theory) be composed of businessmen who had zero employees. The first problem with this exercise is that the number of employees is given only within certain bounds (1, 2, 3,… 10-19, 20-29,… 50- 74,… 75-100,… 350 and over). We address this problem by assuming that – on average – each firm was located mid-way between its particular set of bounds. For example, we assume that firms in the 10-19 category employed 15 workers; this is the most plausible assumption and – in expectation – will minimize the magnitude of any error.

The second problem is that most occupations have a very large discrepancy between the two estimates of total workers (i.e., the estimated number of workers employed is much lower than that enumerated in the census). This implies that many occupations had an implausibly high frequency of businessmen who employed zero workers. For example, in order to reconcile the two estimates of the number of people working as bakers, it would have to be the case that 75 percent of bakers employed no workers. It is possible that 75 percent of bakers employed no help, but it is not the most plausible suggestion. The census therefore seems to be internally inconsistent. An explanation for such inconsistency is offered on p. cclxxvi of the 1851 census itself. Many employers neglected to complete the part of the form asking about the number of their employees. This would lead us to incorrectly assume that all the missing bakers (who were not recorded as employees) were sole proprietors with no employees. This would lead us to overestimate the total number of bakery *businesses* in Great Britain. For example, if a baker employed three people but neglected to note this in his census return, then those three people would end up be counted as three one-man bakery businesses in our calculations. This could make it impossible for us to match the census with trade directories accurately.

We could therefore make one of two extreme assumptions. Either all the missing people in an occupation were one-man businesses; or all the businesses in that particular occupation employed people in the same size distribution that we observe in the table (i.e., for those firms that completed the form). This would be correct if some employers randomly neglected to complete that part of the census return. Logically, the truth will lie somewhere between these two extreme assumptions (i.e., there were actually some Masters who had zero employees and there some who neglected to fill in the form). We made all the calculations that follow using both alternative, extreme assumptions and found that it made no significant difference to our results. How can this be? It is because we are concerned only with the *distribution* of businesses across occupations. If the employers in all trades were equally likely to ignore the part of the form dealing with the number of employees (for example, suppose that 50 percent of all employers failed to complete it), then this will have very little effect on the estimated *distribution* of businesses.

If we make either of these assumptions, then does the census generate an estimate of the business structure that is consistent with the trade directories? Does it suggest that the crowdsourced trade directories are accurate and representative? The census does not report occupational data for every English town, but we can look at a sample of individual towns to shed light on the issue. We downloaded the Chadwyck-Healey pdf version of the 1851 census and matched every town that was reported there against all the available trade directories produced in the years around 1851. This gave us a sample encompassing Whitehaven (Cumberland), Gateshead (Durham), Boston and Lincoln (Lincolnshire), Newark-on-Trent (Nottinghamshire), Kingston-upon-Hull (East Yorkshire), and Leeds (West Yorkshire). We made the calculations described above (based on each of the alternative assumptions) and then compared the total number of businesses estimated from the census to the total number of businesses recorded in the trade directories.[1] The number of businesses recorded in the trade directories was much smaller, showing conclusively that the directories do not offer an exhaustive list of businesses in operation.

However, we are really interested in the *distribution* of businesses across occupations. Were the distributions of businesses across occupations the same in the census and the trade directories? Yes, absolutely. How can we summarize their similarity in some type of descriptive statistic? Calculate the percentage of total businesses constituted by each occupation in both the census and the trade directory. That is, work out what percentage of businesses were bakeries, tailors, taverns, and so on. Now regress the trade directory distribution on the census distribution. What should you expect to find if the trade directory is a random sample of businesses in a particular town? Then a one percent larger share accruing to a particular occupation in the census will be reflected by a one percent larger share accruing to that occupation in the trade directory (i.e., the coefficient on the census data will be unity). So if bakeries and taverns comprised five percent and ten percent respectively of the population of businesses in a town, according to the census, then they should similarly comprise five percent and ten percent respectively of the businesses recorded in the trade directory.

Of course, to the extent that there is measurement error in the estimated occupational structure, the estimated coefficient in the regression will be biased downwards for standard statistical reasons. Hence, we expect to observe estimated coefficients that are less than unity but hopefully not statistically significantly different from it. If the overall distributions are quite similar, then the fit of the regression (the r-squared) will also be high. Note that some of the trade directories that we matched against the 1851 census were compiled several years after the census; we chose them simply because they were the closest years available. Such temporal mismatch would be expected to induce more measurement error and bias the results towards rejecting the hypothesis that the trade directories and the census exhibit the same occupational distribution. Note further that this need not generally be a problem with using trade directories. We are constrained here to find trade directories as close as possible to 1851 because we are undertaking a direct test against the census. If we were given a free choice of year, and were simply trying to assemble a set of trade directories that gave a good coverage, then there would be less temporal mismatch.

We undertook the regression exercise for our sample of towns and found that the distributions of the census and trade directories were very similar for each town, and the coefficient on the census was not significantly different from unity. We report these regressions in Table 1.

[1] A small number of occupational terms used in the census were not used in the trade directory. For example, no business is listed as a "Fustian manufacturer"; since fustian was a type of fine cotton cloth, those businesses were presumably listed as "Cotton manufacturer". The same is true of "Thread manufacturer" and "Calico and cotton printer". We, therefore, aggregated workers in those industries (as reported in the 1851 census) with cotton manufacturers and calculated one multiplier for all branches of the cotton industry that we applied to each of its components (cotton, fustian, thread, and printing). For "Weaver (material not stated)" we took the multiplier to be the average of cotton, flax, and woolen manufacturers. For "Skinner" we took the multiplier to be the average of other occupations in the sub-class (which were all very similar); and the same for "Fuller".

Table 1: Regressing Trade Directory Occupational Shares on Those of the Census, c. 1851

	Coefficient	*95% confidence interval*	r^2	*N*
Greater Birmingham	0.86	0.75 – 0.97	0.71	97
Boston	0.95	0.79 – 1.10	0.70	64
Gateshead	0.91	0.75 – 1.08	0.66	61
Kingston Upon Hull	0.85	0.70 – 1.00	0.65	70
Leeds	0.92	0.82 – 1.03	0.79	82
Lincoln	1.01	0.86 – 1.15	0.73	72
Newark	1.00	0.83 – 1.16	0.71	60
Whitehaven	0.93	0.75 – 1.12	0.57	76
Pooled Sample	0.99	0.90 – 1.09	0.78	119

Notes: We exclude all occupations for which there are zero workers and all occupations for which there is no multiplier available from the table of employees per business. We aggregated "Builders" with "Mason (pavior)" and "Bricklayer"; we excluded "Merchants" because the multiplier in the 1851 table of employees per business is based on only three observations in the entire country; and we excluded the top five and bottom five occupations (in terms of their distance from the occupational share reported in the census) in each town. Our rationale for the last step was that there were a small number of very large outliers that were drastically and randomly skewing the results, and most of these outliers were obviously problematic. For example, "Coal miners" seem to be massively underreported in the trade directories, compared to the census. But this is easily understood when we see that the table of employees per business reports an average of 49 miners per coal mine, which must surely be a drastic underestimate. In general, it was more or less the same 10 occupations that were problematic in each of the towns (notably, "Straw hat and bonnet maker", "Woollen cloth manufacture", "Flax, linen manufacture", "Coal merchant, dealer", "Shopkeeper (branch undefined)" and "Hosier, haberdasher"). The number of observations differs for each regression simply because some towns have more occupations than others.

These results suggest that there is a strong mapping between the business structure revealed by the 1851 census and that reported in contemporary trade directories. This implies that crowdsourcing, when combined with gatekeeping, is an effective way to elicit accurate and representative information – even in a setting with the most rudimentary information technology. We believe that these results offer a satisfactory "proof of principle" of the utility of crowdsourcing. However, the devil may well be in the details and in the final section, where we wrap up, we highlight some key elements.

V. Comparing the Yelp Directory to Government Establishment Data

Yelp is the modern equivalent of the old, paper trade directories. It is obviously a business directory, but we will see shortly that the similarities to the old directories run much deeper than that. We have made an in-depth study of Yelp in Norway and the following discussion is accurate for that market; but the details of Yelp directory construction almost certainly vary across markets

– in response to local laws and data sources – and so we would not want to claim that our characterization is necessarily accurate for all countries. Why choose Norway? In addition to the fact that we are particularly familiar with that market, the Norwegian government is unusually open with microeconomic data pertaining to publicly identifiable units of observation (such as the tax returns of both private individuals and businesses, which are all public information). Amongst the vast ocean of data that the Norwegian government collects – and posts online – is a complete register of all Norwegian businesses. This is crucial for us because it provides an objective metric against which we can judge the representativeness of businesses listed in Yelp. This exercise would not be possible in the U.K. or the U.S., for example, where such a centralized database does not exist or is inaccessible.[2]

Norway is also a nice setting because it is comparable to our historical example in several other dimensions. First, the economies are of similar size – there having been 18 million people in England in 1851 and 5 million people in Norway in 2017. Second, the typical scale of enterprise is very small: 82 percent of Norwegian establishments had fewer than five employees in 2017; in England in 1851, upwards of 44 percent of establishments had fewer than five employees.[3] This is important because you might imagine that large and small firms would have different propensities to list themselves in trade directories. Third, the way that Yelp is compiled is similar to the English historical trade directories. Yelp posts pages for hundreds of thousands of businesses but not all those listings are active. When you find the Yelp page for a business that you know exists, it is often merely a stub and there is no information given except the name and address. It is up to the business owner to claim the listing and then activate it – in the same way that a businessman in 1851 could edit his entry in the draft trade directory in order to add his address and line(s) of business. Fourth, and very importantly, Yelp staff act as gatekeepers: they manually correct information that they believe to be wrong and they can block changes to prevent the infiltration of incorrect information (rather like Wikipedia page editors). In fact, business users sometimes complain that the gatekeepers are too strict in preventing alterations (Kevin, 2012). Fifth, in the case of Yelp, activating the page additionally allows users to post reviews of the business. Yelp then uses artificial intelligence to infer lines of business from customer reviews, thereby using crowdsourced data to adjust for the possibility that owners' classifications may be absent, incomplete, or inaccurate (Tung, 2015). Yelp classifies enterprises into approximately 1,000 different business lines, whereas the 1851 census used a list of 1,089 occupations.

Yelp's business reviews have been a controversial topic (Clark, 2013), particularly the problem of fake reviews. There may be fake positive reviews (primarily business owners posting reviews of themselves, either directly or via employees and relatives); or fake negative reviews (either from people with a personal vendetta against the owner, or from people trying to extort "compensation" – which may or may not be merited – in the form of goods or services). Posting

[2] Although there are accessible, official databases of businesses – for example, the one maintained by Companies House in the U.K. – they do not list all enterprises. For example, Companies House tracks only limited companies (whereas most U.K. enterprises would take the form of sole proprietorships or partnerships). This creates obvious sample selection problems, since enterprises of different sizes and sectors tend to choose different business forms.

[3] The 1851 census gives the number of people employed by "Masters" in around 100 different lines of business. This enables us to calculate the percentage of firms in each businesses line having 2, 3, or 4 employees; we then weight these percentages by the frequency of these lines of business (as reported in the contemporary trade directories) to get our overall estimate of 44 percent. However, note that the 1851 census does not tell us how many Masters had 0 employee (i.e., the establishment had only 1 worker in total – the Master himself), so this 44 percent is a lower-bound figure on the total percentage of business having fewer than 5 workers. It is likely that a high percentage of Masters employed no helpers, so a sensible guess for the total figure could well be around 64 percent.

fake positive reviews is known as "astroturfing". Yelp uses algorithms to try to detect and exclude such reviews, although it is nonetheless estimated that around 20 percent of Yelp reviews are fake (Luca and Zervas, 2016). Reviews tagged by Yelp's filtering algorithm are "parked" and not automatically displayed; Yelp users can choose to view them if they wish, but they are still not used when Yelp calculates its star ratings for each business. Importantly, note that the prevalence of fake reviews need not imply that business ratings are biased, even if the fake reviews were to be included in the calculation of star ratings. Fake reviews tend to be either very positive or very negative, thus making the tails of the review distribution fatter, but the mean could remain unchanged.

Of course, the problem of fake reviews – or news – is by no means limited to Yelp. It is known in the political or cultural arena as "opinion spamming": a highly-motivated minority bombards public bulletin boards with messages favoring a particular candidate or viewpoint – typically concealing their true identity by using multiple aliases – in order to try to lead public opinion in a certain direction (Jindal and Liu, 2008). In auctions, it is known as "shilling": bidders in the pay of sellers enter fake bids to force up the price of an object being offered for sale (Grether *et al*., 2015). It would be perfect if we could find an objective metric of business quality to which we could compare Yelp's star ratings to see just how accurate these crowdsourced review data are. Unfortunately, no one has yet managed to find such a quality metric. What we can do, however, is compare the distribution of businesses on Yelp to the actual distribution of businesses – as revealed by Norwegian government records – to infer whether Yelp at least accurately reflects the pattern of economic activity.

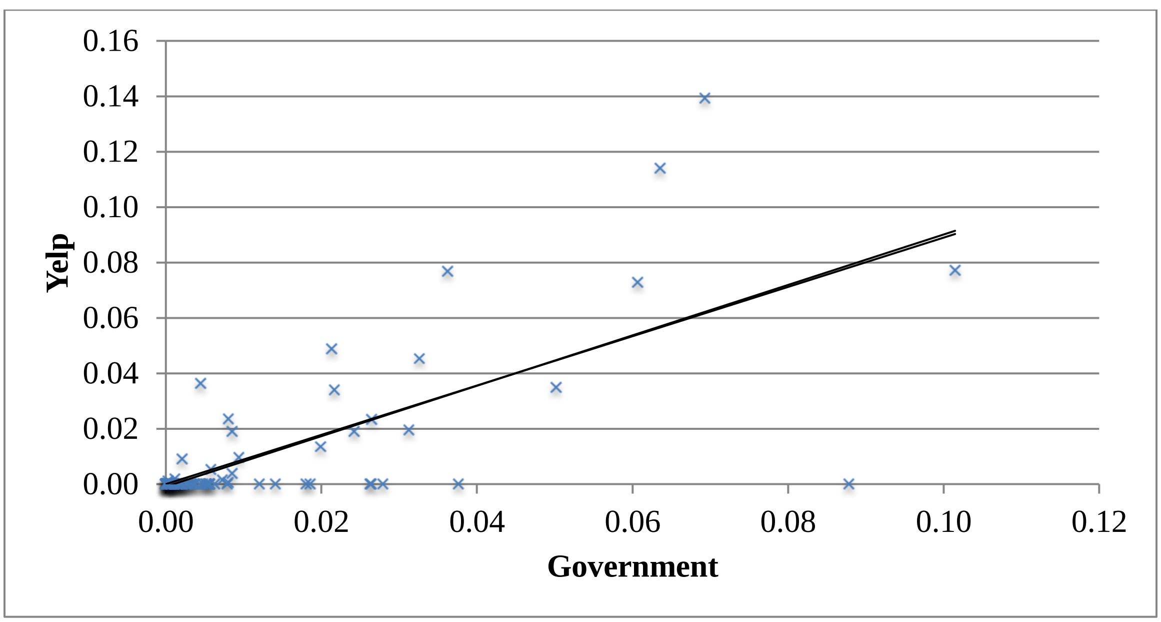
We downloaded the entire database of Norwegian establishments ("virksomheter"), which has a total population of 565,054 (Statistics Norway, 2017). An establishment is defined as "a local kind of activity unit, which mainly conducts activities within a specific industry group". They are classified into 100 different industry groups, from 00 ("Unknown") to 99 ("International organizations and bodies"). We also downloaded the entire Yelp database of Norwegian businesses having an activated page, which is effectively a sample containing 128,011 observations in total. We classified the Yelp data on the same basis as the government establishment data. The interesting question is whether the Yelp sample provides an accurate representation of the Norwegian population. So we proceeded as before, first calculating the percentage of total establishments operating in each of 100 industry groups. We then regressed the percentage reported in Yelp on the percentage reported to the government. If the Yelp sample were truly random, then the coefficient should be unity (a 1 percentage point increase in business frequency in Yelp should map to a 1 percentage point increase in business frequency in the government data) and the intercept should be zero. The basic fit is good: an intercept of zero, a coefficient of 0.86 (±0.17, so not significantly different from unity) and an r-squared of 52 percent.

Figure 2 reveals that there is one very big outlier on the lower right of the graph: the category "Crop and animal production, hunting, and related service activities" constitutes 9 percent of Norwegian enterprises but 0 percent of Yelp businesses. The majority of these enterprises would be family farmers: Norwegian agriculture is characterized by smallholders cultivating a few acres and keeping small numbers of animals. We would not generally expect farmers to be listed in Yelp, so it seems reasonable to exclude that category (and there are no farmers in our 1851 data, so it makes a cleaner comparison). Doing so raises the estimated coefficient to 1.04 (±0.16) and the r-squared to 66 percent. Explaining 66 percent of the variation is respectable, though still inferior to our English results for 1851. This is a little surprising because the English estimation involves an extra step: we multiply the number of firms in each business line by the number of workers per firm in that business line to get an estimate of the occupational structure. We then compare this to the distribution of occupations in the labor census, rather than comparing the trade directories directly to the business census, which we are doing with the Norwegian data. You might expect the extra step to add noise and reduce the r-squared, but it does not seem to do so (or else the Yelp business data are just noisier than the English business data).

Even though Yelp constitutes only a 23 percent sample of Norwegian enterprises (=128,011/565,054) it seems to offer a surprisingly accurate reflection of the distribution of enterprises across business categories (except agriculture). This is consistent with Yelp's own analysis. Their data research team compared the accuracy of Yelp listings to those of competitor sites (such as Google and TripAdvisor) using a hand-collected sample of 1,000 businesses from the U.S. and U.K. (Jason, 2013). Hand-collecting data is obviously time-consuming and expensive: it offers the advantage of very high accuracy but the disadvantage of very small numbers. But if you are trying to judge accuracy against an absolute standard (for example, whether the address, phone number, and website are truly correct) then it is the best strategy. The Yelp team found that their data accuracy was comparable to Google but superior to TripAdvisor and others. We would suggest that Yelp's gatekeeping activity was a crucial component of this success, avoiding the introduction of false information.

In the future, it might be possible to extract firm-specific data (such as the financials, which are publicly available) and take our analysis further by linking them to the Yelp star ratings. It would be interesting, and important, to see whether the crowdsourced star ratings are as accurate as the business categorization, when compared to an objective metric. However, this lies beyond the scope of the current paper.

Figure 2: The Distribution of Norwegian Firms Across Sectors: Government vs. Yelp Data



VI. Discussion and Conclusion

To the best of our knowledge, trade directories represent the first systematic attempt to search for specific information by tapping knowledge embodied in the crowd. It was distinctively different from a census – which was, of course, undertaken in Judaea at least 2,000 years ago – because participation was not compulsory and the information sought did not necessarily pertain to the individual who was reporting it. Our historical scenario shares many key characteristics with modern crowdsourcing – such as the fact that it was a commercial undertaking (and hence participation was voluntary), that accuracy was important, and that the entrepreneur was building up a mosaic of data.

Analysis of both historical and modern data suggests that there is a very tight mapping from crowdsourced (sampled) data to government (population) data – that is, from trade directories to the census. But this may not be a general result for crowdsourced data. The compilers of trade directories have structured their search in clever ways to elicit a broad contribution of accurate information. Businessmen have an incentive to include truthful information about themselves, and gatekeepers have been on hand to discourage the contribution of false information. Contributors have been working within a framework previously formulated by the directory creators (Yelp in the modern setting, Wilkes and the local printers and publishers in the historical setting). The overall structure of the information elicitation scheme is similar to Wikipedia – accepting contributions from the largest possible crowd and then having gatekeepers weed out bad information. Importantly, each piece of information is parsed by multiple members of the crowd, so individual errors are likely to be eliminated (more like Galton, less like researchers who rely on only one member of the crowd to categorize data). The modern and historical directories both seem to accurately reflect the structure of economic activity. However, the reliability of Yelp's more advanced functions – particularly its review and rating system – remains an open issue.

It may seem surprising that crowdsourcing was feasible before the internet age. The cost of contributing was higher because you had to go to the location in person to adjust the record with a pen. Of course, one aspect of our historical setting is that the information collected was local (people were offering information about themselves and their neighbors), which kept the contribution cost low (no one had to travel a great distance to contribute). But, in fact, the non-zero cost of contributing may well have been an advantage: it is plausible that people are less likely to volunteer false or inaccurate information when it is costly to do so. You might write a fake Yelp review from the comfort of your sofa, but you are less likely to bother if you must walk to the other end of town to do it, and then have to hand it to someone who may notice that it is fake. Trade directories demonstrate that crowdsourcing can be an effective way of collecting a vast amount of accurate information. But the design of the information elicitation scheme is likely to prove crucial and there can be no general presumption that crowdsourced data are accurate, truthful, or representative. Given the vast quantity of crowdsourced data becoming available, we need to think very carefully about what – if anything – we can reliably infer from it.

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