Original Article

Role of demographics, social connectedness and prior internet experience in adoption of online shopping: Applications for direct marketing

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ABSTRACT The use of demographics by researchers in the online shopping literature is common, however, they are typically constructed as either moderators or control factors. Little attention has been given to explicitly modelling the predictive utility of demographics. The present research models the impact of nine demographics, six social connectedness measures and five prior online experience variables on consumers' actual online purchases. A large and representative data set was used. Our results show that a model on the basis demographic data alone explains 22.6 per cent of the variance in the consumers' overall online shopping behaviour. The model's utility increased to 45.4 per cent once social connectedness and prior internet experience were added to the model. Furthermore, analysing 14 online product categories, we found that the predictive power of demographic variables is product specific. Overall, our results strongly support the use by practitioners of demographics as powerful predictors for direct targeting of online shoppers.

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Keywords: online shopping; demographics; prior internet experience; social connectedness; empirical studies; predictive utility

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INTRODUCTION

The continued growth of online shopping sales has stimulated great interest in this field of scientific inquiry. According to ACNielsen[1] over 875 million individuals have shopped online worldwide, and it is predicted that combined online sales in the United States and Western Europe will reach US$407 billion by 2014.[2] Demographic variables are among the multitude of factors that have been widely used by researchers to discriminate online buyers from non-buyers and results of past studies generally suggest that demographics have significant impact on internet shopping behaviour.[3–11] Given that demographic variables are readily available, cost-effective and that demographic-based models can be quickly developed and deployed to solve emerging business problems,[12–14] better understanding of the predictive power of them is critical, particularly for those organisations with significant direct marketing and database marketing operations.[15]

Although studies of demographics are widespread in the literature, they have generally constructed demographics as either moderators or control factors.[16–18] Research that explicitly models the predictive power of demographic variables is scarce. Extensive review of online shopping literature by Chang, Cheung and Lai[19] shows that there is no one dedicated study in the literature that examines the predictive utility of demographic variables. As such, the explanatory power of demographics is still not well understood or appreciated, particularly at product level, and further research is needed to address this shortcoming in the literature. Furthermore, except for age, gender, income and education, studies that examined the impact of other demographics on online shopping are rare and reported finding are inconsistent.[19,20]

This article seeks to add value to the literature in four key areas. First, we explore the impact of nine demographic variables on online shopping behaviour. The effects of some of these demographics such as language skills, occupation, marital status, household size and country of birth have seldom been investigated in past studies.[19] Second, prior studies have generally focused on attitudes towards online shopping and intention to shop online.[3,21–25] Empirical evidence in relation to consumers' actual online purchases, which is more relevant to real-life applications, is relatively rare. Moreover, there is limited research that has explored such behaviour at product level. To address these gaps in the literature, the current study examines actual purchases of 14 narrowly defined online goods and services. Third, this study contributes to the literature by exploring the effect of social connectedness on actual online shopping. In the past, Sultan, Farley and Lehmann[26] meta-analysed the diffusion of innovation literature involving results of 213 Bass models and found that interpersonal channels of communication are the major drivers of diffusion of innovation, which implies that socially connected consumers are more likely to adopt. However, the impact of social connectedness on internet shopping has not been thoroughly investigated. The current study fills this gap in the literature. Fourth, we contribute to the literature by providing further empirical evidence in relation to the impact of prior online experience on actual online purchase.

The inclusion of social connectedness and prior experience in our study is guided by the fact that, like demographics, these variables are also readily available or can be collected at reasonable cost. As such, these variables can be combined with demographics to develop powerful data-mining models for practical business applications, in particular selecting customers that are more likely to purchase or respond to database marketing and direct marketing. Data-mining models, as opposed to theory-based models, are indeed in common, and growing, use among practitioners. In a survey of the 500 fortune companies, Calderon, Cheh and Kim[27] found that about 65 per cent have implemented some form of data-mining models. According to Hair,[28] businesses and organisations are increasingly shifting towards use of data-mining models to solve business problems and pursue opportunities.

The remainder of this article is organised as follows. First, we review the relevant literature and develop the research hypotheses. Next, we discuss the research methodology and then present the findings. We conclude with discussion of implications, future research avenues and limitations.

LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Demographic determinates of online shopping

Our research conceptual model is shown in Figure 1. The model illustrates the hypothesized relationships among demographic variables, social connectedness, prior online experience and actual purchase of 14 online product categories. Age is among the most widely used demographics in the online shopping literature.[19] It is generally found that increasing consumer age has a negative impact on the adoption of online shopping.[4,29] It would appear that older consumers are lower in innovativeness[30,31] and, as such, are less likely to adopt e-commerce. Older consumers also appear to enjoy the social experience and the diversion associated with in-store shopping. Dholakia and Uusitalo[32] found that older individuals perceive a higher hedonic benefit for in-store shopping than younger people. Finally, older consumers are generally less familiar with computers,[32] which arguably results in higher computer anxiety and lower self-efficacy, hence lesser chance of shopping online. Thus, we propose the following hypothesis:

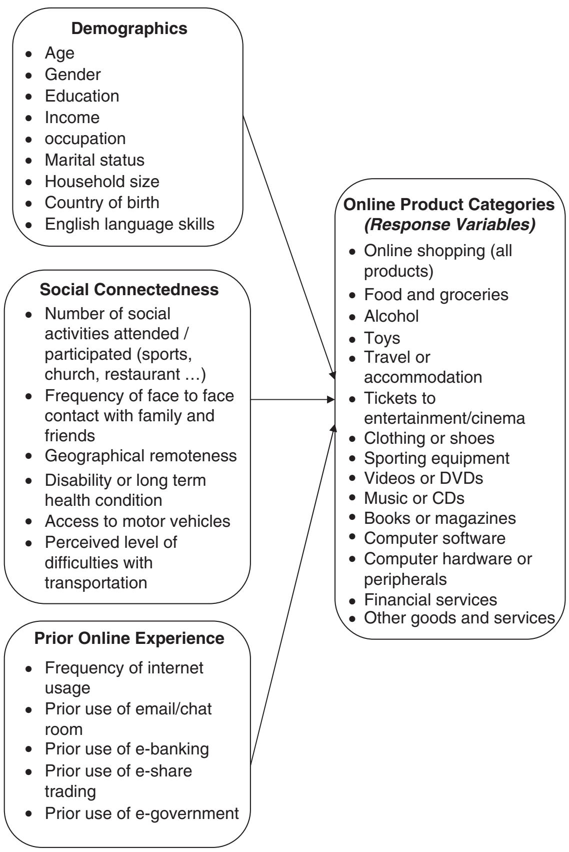

Figure 1: Research conceptual model.

Hypothesis 1: Age exerts a negative influence on online purchase of goods and services.

Prior research examining the effect of gender on willingness to shop online revealed that men are more likely to conduct online transactions than women.[3,4,7–11] There are some studies where opposing, or mixed, conclusions were reported; however, these appear to be exceptions to the general pattern, such as the purchase of clothing by women.[5,33] Several explanations have been advanced in the literature for the gender differences including risk perception,[34] a general attitude towards technology[35] and differences in role specializations.[36,37] Perhaps, the most widely investigated reason is that women appear to be more concerned with risk associated with e-commerce than their men counterparts.[11,38,39] This explanation is consistent with the earlier studies which found women were also more risk averse in other domains including medical, environmental and financial matters.[40–42] We therefore posit the following hypothesis:

Hypothesis 2: Men are more likely to purchase online goods and services than women.

Empirical findings indicate that better educated individuals are more likely to favour online shopping,[7,9] purchase more frequently and spend more online.[43] Burroughs and Sabherwal[43] identified two ways in which one's education contributes to adoption of retail electronic purchasing. They argued that, by increasing the perceived ability to deal with uncertainty, as well as enhancing computer self-efficacy, education would increase the likelihood of online shopping. The concept of self-efficacy has been extensively investigated[6,44,45] and defined as one's belief in his or her ability to accomplish a task.[46,47]

Self-efficacy was found to be positively associated with online shopping and internet banking.[48,49] Given that online shopping generally involves a significant amount of cognitive and behavioural skills, it would appear that better educated individuals are more likely to have the necessary confidence to face this task. Therefore, we hypothesise that:

Hypothesis 3: Education and online purchase of goods and services are positively associated.

It is suggested that household income positively influences adoption of online shopping[4,9] and, perhaps unsurprisingly, has a positive impact on the frequency and amount spent online.[8,11,43] in addition, income was found to exert a positive influence on the intention to shop via internet.[7] Kinsey[50] utilised the so-called New Theory of Consumer Behaviour[51,52] in an attempt to rationalize the relationship between income and consumers' shopping behaviour. He noted that as the value of time increases, households tend to use the least time-intensive medium of exchange (that is, credit card) in order to minimize households' cost of producing a given level of shopping services. He argued that, other things being equal, using credit card, as the least time-intensive medium of exchange, 'would increase the marginal productivity of time … in producing shopping services, allowing more goods to be purchased per unit of time' (p.173). By analogy, when the cost of non-market time is high, a rational consumer would use the least time-intensive channel of shopping (that is, non-store shopping environments such as internet) to reduce the overall cost of shopping. Following Kinsey,[50] we assume that cost of non-market time is positively associated with income levels.

The literature also links 'time pressure' to web shopping arguing that those who work extended hours are more inclined to shop online.[53,54] Given that higher income earners typically work longer hours, it seems not only that the 'value of non-market time', but also the 'lack of time' contributes to greater interest among more affluent consumers in online shopping. There are also other possible explanations for the impact of income on online shopping. For instance, affordability has been linked to online shopping behaviour.[43] By far most of the popular products offered online have been discretionary items (for example, travel, holidays and entertainment) which are suitable for affluent consumers with higher disposable incomes.[55] Higher income is also associated with access to faster internet which, in turn, has shown to facilitate online shopping decisions.[43,54] Meanwhile, the online literature has linked financial risk to adoption behaviour as well. Dickerson and Gentry[56] postulated that financial risk of adoption is higher for low income earners and thus negatively affects their behaviour. This is particularly the case for online shopping where the financial risk is seemingly substantial because of a number of concerns including credit card fraud, inability to examine products before purchasing,[54] and difficulties related to cancelling orders and receiving refunds.[25] We therefore propose the following hypothesis:

Hypothesis 4: Income and online purchase of goods and services are positively correlated.

Overall, a review of online shopping literature by a number of authors[19,20] suggests that demographic characteristics are among the significant contributors to acceptance of online shopping. However, except for age, gender, income and education there is little empirical evidence in relation to the effects of other demographics on internet shopping. Intuitively, one would expect that individuals with managerial or professional jobs are more inclined to purchase online because they have higher income. Karjaluoto, Mattila and Pento[6] have found that being in high status level occupations is associated with positive attitudes towards online banking. Past studies suggested that being married and the number of children have a positive impact on the adoption of mobile phones.[57] Brown and Venkatesh[17] found a strong moderation effect from marital status and household size on online shopping. Thus, we expect to see a positive relationship between being married, household size and the purchase of online goods and services. There are two reasons that married couples and larger households would purchase online. First, they are more likely to be dual income earners having more disposable income. Second, married couples and larger households are more likely to involve children and, as such, time becomes more valuable and the cost of conventional shopping increases. It is also conceivable that English language skills would facilitate the adoption of online shopping by reducing online shopping risk and making available a wider choice of online products. Peres, Muller and Mahajan[58] suggested that the utility of adoption of a product is positively related to the total number of adopters. In this case, English-speaking consumers constitute a larger online market which in turn, increases the utility of adoption of online shopping for potential English-speaking adopters by increasing the available number of online vendors and products. As a result, we would expect a higher online shopping adoption rate among native English-speaking Australians or migrants from English-speaking countries. Therefore, we propose the following hypothesis:

Hypothesis 5: Being in a managerial or professional occupation increases the likelihood of online purchase.

Hypothesis 6: Married customers are more likely to purchase online than never married, widowed, separated and divorced customers.

Hypothesis 7: Household size has a positive impact on the likelihood of buying online.

Hypothesis 8: Migrants from English-speaking countries have a higher likelihood of shopping online.

Hypothesis 9: Proficiency in English language positively influences the probability of shopping online.

Social connectedness

Dickerson and Gentry[56] noted that the literature often envisage innovators as socially integrated and as belonging to more social groups. Wyckhuys and O'Neil[59] studied adoption of a new pesticide among small-scale maize farmers and found that adopters were socially well connected. Recently Liu, Madhavan and Sudharshan[60] demonstrated that new product managers are able to accelerate the diffusion rate by re-designing the underlying network structure for example, by artificially connecting the opinion leaders, users and potential users via teleconferences. It is perceivable that social connectedness facilitates the spread of word-of-mouth, which has been found to have strong influence on the adoption of an innovation. Rogers[61] argued that interpersonal channels of communication are the main drivers of adoption for all categories of adopters except for innovators (that is, early adopters, early majority, late majority and laggard). Empirical findings are supportive. In a meta-analysis, Sultan, Farley and Lehmann[26] analysed results of 213 Bass[62] models published in the literature and found that the average values for coefficient of innovation (p) and coefficient of imitation (q) were 0.03 and 0.38, respectively, indicating that word-of-mouth is the main deriver of diffusion of new products. Naseri and Elliott[63] investigated the diffusion of online shopping in Australia and found that the coefficient of innovation (p) and coefficient of imitation (q) were 0.033 and 0.384, respectively, indicating, again, that adoption of online shopping is fundamentally driven by word-of-mouth. Further, it is likely that social connectedness facilitates transmission of social signals which clarifies to individuals the consumption behaviour of people in their aspiration group.[58]

Drawing on the past studies, we propose that consumers who are more socially oriented would be more influenced by the pressure of two social forces namely word-of-mouth and social signals. Therefore, they are more likely to adopt online shopping then the less socially connected consumers. As a result we expect to see a positive association between social connectedness and adoption of online shopping. For the purpose of this study, we use six variables as surrogates for social connectedness. The number of social events attended or participated in (for example, attended church, participated in sports events and so on.) and the frequency of face-to-face contact with family and friends are assumed to increase consumers' exposure to word-of-mouth and social signals and should have a positive impact on the adoption of online shopping. Conversely, living in a geographically remote area and factors that restrict consumers' participation and physical presence in the community such as disability and limited accesses to motor vehicles would reduce exposure to word-of-mouth and social signals, and as a result, are expected to have negative impacts on the adoption of online shopping. On the basis of the foregoing arguments we propose the following hypotheses:

Hypothesis 10-a: Number of social activities attended/participated has a positive impact on the online purchase of goods and services.

Hypothesis 10-b: Frequency of face-to-face contact with family and friends has a positive impact on the online purchase of goods and services.

Hypothesis 10-c: Geographical remoteness has a negative impact on the online purchase of goods and services.

Hypothesis 10-d: Disability or long-term health condition has an adverse impact on the online purchase of goods and services.

Hypothesis 10-e: Access to motor vehicles has a positive impact on the online purchase of goods and services.

Hypothesis 10-f: Perceived Level of difficulties with transportation has a negative impact on the online purchase of goods and services.

Impact of prior internet experience

The theoretical conceptualisation of the effect of prior online experience on web shopping has been developed along three lines of thinking. First, it is arguable that having prior experience with the internet would significantly decrease the amount of time and cognitive efforts involved in both learning and conducting web shopping and thus should lead to a higher likelihood of online purchase. Koyuncu and Lien[9] argued that experience with the internet would reduce the time needed to navigate websites and search for information thereby increasing the probability of online purchase. Similarly, Citrin *et al*[64] suggested that broader experience with the internet would provide users with the necessary skills and confidence for trying web shopping. Second, the results of the past studies have shown that prior experience with the internet reduces the perceived risk of online purchase.[65] Consequently, and unsurprisingly, prior use of the internet should positively contribute to the higher propensity of online shopping. Third, the theory of diffusion of innovations[61] holds that compatibility of an innovation with previously introduced ideas would facilitate the adoption of the new ideas. Potential adopters generally use the older innovations to assess the new innovations. In the context of online shopping, past web browsing experience, particularly non-shopping activity such as e-banking, e-share trading and e-mail/chat rooms can be used to judge online shopping in terms of risk involved, functionality, usefulness and outcomes.

Empirical evidence suggests that the frequency of internet use is positively related to online shopping.[4,45] Furthermore, Citrin *et al*[64] noted that online shopping has been more common among those who use the internet for a greater number of non-shopping applications (for example, communication, education, business and entertainment). Therefore, based on the forgoing discussion we propose the following hypotheses:

Hypothesis 11-a: Frequency of internet use is positively associated with online shopping.

Hypothesis 11-b: Use of e-mail/chat room, is positively associated with online shopping.

Hypothesis 11-c: Prior experience with e-banking is positively associated with online shopping.

Hypothesis 11-d: Prior experience with e-share trading is positively associated with online shopping.

Hypothesis 11-e: Prior experience with e-government is positively associated with online shopping.

METHOD

Data

Data for this study are drawn from General Social Survey 2002 (GSS02), which was carried out by the Australian Bureau of Statistics from March 2002 to July 2002.[66] Out of 17 000 potential respondents, 15 510 responded adequately resulting in a 91 per cent response rate. The response rate seems to be reasonably high compared to the similar studies, which appear in the literature, although this may be normal for data collected by government statistical bodies. Gender distribution in the sample was fairly even, with men accounting for 49.5 per cent of the sample. In terms of age, 13.1 per cent were 18–24 years; 20.0 per cent were 25–34 years; 20.2 per cent were 35–44 years; 18.2 per cent were 45–54 years; 13.0 per cent were 55–64 years and 15.4 per cent were over 65 years. The average age of respondents was 45 years. About 64.1 per cent of respondents were employed full-time or part-time. Annual household income was approximately A$33 000. About 27.6 per cent of respondents were born overseas.

A preliminary analysis showed that the adoption rates of online shopping for most of the products were typically low. This generally causes logistic regression to classify most of the observations in the larger cell, the non-buyers in this case.[67] To avoid this problem, referred to as unequal cell-size problem, we over sampled the number of buyers thus creating a nearly symmetrical distribution of buyers and non-buyers. For example, out of 15 510 respondents, 287 (1.9 per cent) had purchased food and groceries online. To create a sample with an equal number of buyer and non-buyers, we randomly selected 287 respondents from 15 223 non-buyer respondents; hence a symmetrical sample. This process was repeated for all 14 online product categories. The method, known as 'salting', has been recommended in the direct marketing context[68] and appears to provide results which are straightforward and easy to understand.[69] In practice, one needs to re-scale the resulting probabilities to reflect the proportion of buyers and non-buyers in the original sample which can be carried out readily by most of the commercial statistical software such as SAS E-miner.

Variables

Adopters of online shopping (the dependent variable) were defined as those who purchased goods or services online during the past 12 months. There were 14 product categories hence 14 dependent variables. It should be noted that the term 'online purchase' was broadly defined in the GSS02 and includes online orders, which were paid off online, as well as orders paid off fully or partially off-line. All of the dependent variables are measured as binary variables (adopters = 1, non-adopters = 0). Appendix shows the definitions and the coding scheme of the independent variables.

RESULTS

In this section we first present the impact of demographics, social connectedness and prior online experience on the overall actual online shopping behaviour, followed by a detailed analysis of the impacts of demographic variables on the actual purchase of 14 online product categories. It should be noted that we did not include interaction terms in the research model because of the fact that, to our best knowledge, there is no underlying theory or conceptual framework that guides inclusion and interpretation of such terms.

Demographics and actual online shopping behaviour

Table 1 presents the result of the hierarchical logistic regression analysis. Model 1 is the 'base' model with the nine demographics all included in the equation. The model's χ^2 is significant ($\chi^2 = 2199.5$, $P < 0.000$). Moreover, the coefficient of determination (R2) indicates that 22.6 per cent

Table 1: Results of hierarchical logistic regression analysis

Independents	*Demographic model*	*Full model*	*Hypothesis*
Demographic			
Age	−0.167**	−0.083**	H1
Gender	0.150**	0.116*	H2
Education	0.344**	0.127**	H3
Income	0.197**	0.131**	H4
Occupation	−0.731**	−0.288**	H5
Marital status	−0.340**	−0.076	H6
Household size	−0.040	−0.076	H7
Country of birth	0.176	−0.366	H8
English language skills	−0.578**	−0.229	H9
Web Experience			
Frequency of internet usage	—	0.237**	H10-a
E-mail/chat room	—	1.333**	H10-b
E-banking	—	1.013**	H10-c
E-share trading	—	0.433**	H10-d
E-government	—	0.219**	H10-e
Social Connectedness			
Number of social activities	—	0.130**	H11-a
Frequency of face-to-face contact with family and friends	—	−0.089	H11-b
Geographical remoteness	—	0.048	H11-c
Disability or long-term health condition	—	0.070	H11-d
Access to motor vehicles	—	0.052	H11-e
Perceived level of difficulties with transportation	—	−0.227*	H11-f
Model χ^2	2199.5	4795.7	—
	(*P*-value=0.000)	(*P*-value=0.000)	—
Nagelkerke R^2	0.226	0.454	—

*significant at 95% level.
**significant at 99% level.

of variation in the adoption of online shopping was accounted for by the nine demographic variables included in the model, suggesting that the demographic model describes the respondents' actual adoption behaviour reasonably well. The result of Hosmer & Lemeshow test,[70] which assesses how closely the observed and predicted probabilities match, is not significant ($\chi^2=11.14$, $P=0.194$) pointing to a good fit to the data.

The results of Model 1 suggest that probability of adopting online shopping is significantly decreased as consumers' age increases ($\beta=-0.167$, $P<0.000$). Thus, Hypothesis 1 is supported. Hypothesis 2 which postulates that men are more likely to adopt e-commerce than women was also supported ($\beta=0.150$, $P<0.000$). As expected, both education (Hypothesis 3) and income (Hypothesis 4) exert a significant and positive impact on the adoption of e-shopping ($\beta=0.344$, $P<0.000$; $\beta=0.197$, $P<0.000$, respectively). That is the higher the education and income the higher the probability of being online shopping adopters. Both hypotheses (Hypothesis 3 and Hypothesis 4) were supported. Similarly, consumers in managerial/professional occupations exhibited greater propensity to adopt online shopping ($\beta=-0.731$, $P<0.000$). Thus, Hypothesis 5 is supported. The findings also suggest that adopters of consumer e-commerce are more likely to be married/couple than never married/widowed/separated/divorced ($\beta=-0.340$, $P<0.000$). Hypothesis 6 was supported. No evidence was found to support the effect of household size on overall adoption of online shopping and therefore, Hypothesis 7 was rejected ($\beta=-0.040$, $P>0.05$). We also found that country of birth (Hypothesis 8) had no significant impact on tendency to purchase online ($\beta=0.176$, $P>0.05$). Finally, support was found for Hypothesis 9 ($\beta=-0.578$, $P<0.000$) indicating that the likelihood of adoption of online shopping was lessened by poor English language skills.

Impacts of social connectedness and prior internet experience

Model 2 includes the nine demographic variables from the 'base' Model 1 plus measures of social connectedness and prior online experience (Table 1). Of the nine demographics only five core variables that is, age, gender, income, education and occupation have statistically significant impacts on the actual online shopping beyond the effects of other demographics, social connectedness and prior online experience variables.

Of the six social connectedness measures included in the model only two, namely the number of social activities attended or participated (for example, sports events, churches) and perceived level of difficulties with transportation appeared to have significant impacts on the incidence of online shopping. The results therefore suggest that socially active consumers are more likely to purchase online ($\beta = 0.130$, $P > 0.000$). As hypothesised, perceived level of difficulties with transportation had an adverse impact on web shopping ($\beta = -0.227$, $P > 0.05$). Thus Hypothesis 10 is partially supported.

Model 2 also includes five 'web experience' variables: namely, frequency of internet usage, use of e-mail or chat room, e-banking, e-share trading and e-government. As predicted by the Hypothesis 11-a to Hypothesis 11-f, all of the web experience measures are positively and strongly associated with the adoption of web shopping. Therefore, Hypothesis 11 is supported. It is worth noting that adding web experience and social connectedness substantially increased the model's explanatory power from 22.6 to 45.5 per cent.

Impacts of demographics on purchase of online product categories

Table 2 depicts the overall fit measures for the logistic regression models developed for the 14 online product categories. The models' χ^2 are all significant. Further evidence of fit is given by the Hosmer & Lemeshow test.[70] Except for two models (that is, financial services and computer hardware) the χ^2 values are not significant which indicates reasonable fit to the data. This test is sensitive to sample size and tend to be significant when sample size is relatively large as is the case with these two models.

Table 3 shows the direction of relationships between the nine demographic variables and 14 online product categories. Several key findings emerged from this analysis. First, based on the frequency of being significant, five demographics namely occupation, gender, income, age and education appear to be the most important determinants of online shopping behaviour. These variables were significant in 11, 10, 9, 8 and 6 models out of 14 models, respectively. Second, demographics show a reasonable predictive power across all the product categories with the percentage of correct calcification (PCC) ranging from 65.7 to

Table 2: Overall results of binary logistic regression analysis

Ref	Dependent variables	Sample size	Models' χ^2: P-value	Hosmer & Lemeshow Test: P-value	R^2	Maximum chance criterion	Hit ratio
1	Food and groceries	572	0.000	0.528	0.396	50.3	73.4
2	Alcohol	188	0.000	0.103	0.500	50.5	80.3
3	Toys	253	0.000	0.951	0.401	50.2	72.7
4	Videos or DVDs	547	0.000	0.510	0.391	50.3	73.5
5	Music or CDs	786	0.000	0.572	0.340	50.5	71.0
6	Books or magazines	1445	0.000	0.105	0.311	50.2	69.1
7	Financial services	678	0.000	0.037	0.378	50.7	73.5
8	Computer hardware or peripherals	446	0.000	0.035	0.403	50.4	74.7
9	Computer software	997	0.000	0.087	0.316	50.1	68.8
10	Clothing or shoes and so on	675	0.000	0.380	0.396	50.1	72.6
11	Sporting equipment	277	0.000	0.208	0.408	50.5	74.4
12	Travel or accommodation	2412	0.000	0.671	0.350	50.0	72.9
13	Tickets to entertainment or the cinema	1217	0.000	0.735	0.387	50.5	72.5
14	Other goods or services	937	0.000	0.896	0.208	50.6	65.7

Table 3: Results of logistic regression analysis by product categories

Model	*Dependent variables*	*Age*	*Gender*	*Marital status*	*Household size*	*Education*	*Income*	*Occupation*	*Country of birth*	*Language skills*
1	Food and groceries	+ +/c	+ +/inc	ns	ns	ns	ns	ns	ns	ns
2	Alcohol	ns	ns	ns	+/c	ns	ns	+ +/c	ns	ns
3	Toys	ns	ns	ns	+/c	ns	ns	ns	ns	ns
4	Videos or DVDs	+ +/c	+ +/c	ns	ns	ns	+ +/c	+ +/c	ns	ns
5	Music or CDs	+ +/c	+/c	ns	ns	+ +/c	ns	+ +/c	ns	ns
6	Books or magazines	+ +/c	ns	ns	ns	+ +/c	+ +/c	+ +/c	+ +/c	ns
7	Financial services	ns	+ +/c	ns	ns	+ +/c	+ +/c	+ +/c	ns	ns
8	Computer hardware or peripherals	ns	+ +/c	ns	ns	ns	+/c	+/c	ns	ns
9	Computer software	ns	+ +/c	ns	ns	+ +/c	+ +/c	+ +/c	ns	ns
10	Clothing or shoes and so on	+ +/c	+ +/inc	ns	ns	ns	+ +/c	+ +/c	ns	ns
11	Sporting equipment	ns	+ +/c	ns	+/c	ns	ns	ns	ns	ns
12	Travel or accommodation	+ +/c	ns	ns	+/c	+ +/c	+ +/c	+ +/c	ns	ns
13	Tickets to entertainment or the cinema	+ +/c	+/inc	ns	ns	+ +/c	+ +/c	+ +/c	ns	ns
14	Other goods or services	+/c	+/inc	ns	ns	ns	+/c	+ +/c	+/c	ns
	Frequency of being significant variable in the models	8	10	0	4	6	9	11	2	0

c; consistent with the research hypothesis.

inc; inconsistent with the research hypothesis.

+ $P<0.05$, + + $P<0.01$, results based on likelihood ratio test.

85.1 per cent. Third, the predictive power of demographics appears to be product-specific. For instance, although household size is considered to be a less important variable by the above mentioned standard, the probability of purchasing toys over the Internet can be better predicted by this variable (R-square=0.50, hit ratio=80.3 per cent) then the other demographics. In fact, the other eight demographics are shown to exert no significant influence on the adoption of online purchase of toys once the effect of household size was controlled. Fourth, with regard to the sign of regression coefficients, they are largely in line with the expected patterns as outlined by the research hypotheses. However, gender is clearly a notable exception. The results show that the sign of regression coefficients for gender changes across the product categories. More specifically, adopters of 'food and groceries', 'clothing and shoes', 'ticket to entertainment, cinema' and 'other goods and services' were more likely to be woman than man.

DISCUSSION

The purpose of the present research is to develop and validate a demographically-oriented data-mining conceptual framework. First, we are interested to understand whether demographic variables possess enough predictive power to solve real-life business problems, in particular, identifying consumers that are more likely to buy online. Our results show that demographics alone explain a modest 22.6 per cent of the variance in the consumers' actual usage of online shopping channel. Adding prior online experience and social connectedness to the equation increased the model's utility to a respectable 45.4 per cent. This is a very reasonable predictive power for behavioural research and can be favourably compared to the predictive power of traditional theory-based models. In this context, Venkatesh *et al*[16] reviewed eight well-established models including the technology acceptance model,[71–73] the theory of planned behaviour[75,76] and the innovation diffusion theory[61] and found that they explain between 17 per cent and 53 per cent of the variance in users' intentions to use information technology. Other work has found that theory-based models explain 26 per cent of the variance in consumers' actual online shopping behaviour and 40 per cent of the variance in consumers' intention to buy online.[74]

Second, we found, through our analysis of 14 online products, evidence that the predictive powers of the demographic models developed in this study are in fact product-specific. Our model with nine demographic variables explains between 31.1 per cent (books and magazines) and 50.0 per cent (alcoholic beverages) of the variance in actual adoption of online shopping, which clearly indicates that the explanatory power of demographic variables could differ by product types. It is plausible that the variation in the predictive power of demographic models caused by the fact that product-specific models need to simultaneously model purchase of a given product and usage of online channel. In other words, online alcoholic beverages model, for example, models the likelihood of purchase of alcoholic beverages, as well as usage of online shopping channel by consumers. As such, relatively lower predictive power of some of the models (for example, books and magazines) perhaps is because demographics are not suitable to predict purchase of such products.

Further to that, our analysis also revealed that purchase of certain online products may be better predicted by some particular demographics. For example, purchase of food and groceries is better predicted by age and gender whereas online purchase of toys is more closely correlated with household size. From a theoretical perspective, this means that demographic models might have limited ability to be generalised across various products.

Third, our analysis failed to find any major evidence that the direction of the effect of the demographic variables is product-specific. Online shoppers were generally highly educated, young, affluent and professionals regardless of the types of the products they purchase (for example, CDs or financial services). Gender is the only notable exception as its direction of effect differs by product category. It is found that online buyers of food and groceries, clothing and shoes and entertainment services were more likely to be women as opposed to online buyers of DVDs, CDs, financial services, computer hardware and software and sporting equipment, who tended to be men.

Fourth, the current study found strong evidence of the effect of web experience on online shopping. That is, probability of online shopping was significantly higher among consumers who more frequently used the internet, e-mail or chat rooms and had e-banking, e-share trading and e-government experience. Another interesting finding emerged from this study suggesting that the probability of shopping online differs by the level of social connectedness. Consumers who attended or participated in a greater number of social events were more disposed to purchase online. In addition, as was hypothesised, perceived level of difficulty with transportation had an adverse impact on the probability of web shopping, indicating that less mobile consumers are less inclined to buy online perhaps because of lesser exposure to word-of-mouth and social signals. However, in contrast, our analysis failed to reveal any relationship between other indicators of social connectedness, such as the frequency of face-to-face contact with family and friends, disability or long-term health condition – and online purchase.

Hence, what do all these mean for direct marketing? At a fundamental level, our results provide strong support for the use by practitioners of demographically oriented models as a powerful substitute for traditional theory-based models. The results of the current study clearly demonstrate that the predictive power of demographic variables is sufficient to effectively discriminate online buyers from non-buyers and, as such, to develop profitable direct marketing campaigns. More interestingly, the results show that for most online product categories, information on five core demographics that is, age, gender, income, education and occupation would be sufficient to develop a reasonable predictive model. Alternatively, direct marketing practitioners may combine demographics with other readily available variables such as consumers' prior use of the internet and social activities to create an even more powerful demographically-oriented predictive model. Practitioners, however, should be mindful of the limitations of demographic models as well. As discussed earlier, the predictive power of demographics varies by product categories, which means that a demographic model which is developed to target online buyers of wine may not have similar predictive power when it comes to targeting online buyers of books and magazines. Moreover, although five core demographics (that is, age, gender, income, education and occupation) are typically good predictors of online shopping, there are some exceptions to this finding. For instance, the appropriate demographic variable to predict online purchase of toys is household size. Thus, depending on product type, practitioners may need to recalibrate their demographic models via selecting appropriate variables.

Overall, the results of this study would suggest that, beyond the use of demographic variables, the use of more 'sophisticated' constructs (for example, innovativeness) and models (for example, the theory of planned behaviour), may not be justified in terms of incremental improvement in models' discriminatory power. Furthermore, with the incremental cost of developing and applying such models, the case becomes even more problematic. Of course, it was always so. This study, however, provides empirical evidence that the cost-benefit argument for increasingly sophisticated theory-based predictive models is not proven.

LIMITATIONS AND DIRECTIONS FOR FUTURE RESEARCH

Although the results of this study show that demographic information is important for predicting consumer online shopping behaviour, it may not be clear why such information is important and how it influences the consumer behaviour. The present study identifies several factors that can be potential mediators for demographic variables, such as self-efficacy,[48,49] cost of non-market time[50] and risk concern.[11,39] Future work should attempt to empirically test the mediation effects of these factors. This would help us to have a deeper understanding of the process by which demographics affect online shopping behaviour.

The variance explained by the demographic models developed in this study is quite high given the amount of information contained in such a simple model. Future research should investigate other potential demographics, such as the presence and number of children in family, the age of children and retirement. In particular, Household Life Cycle (HLC)[77,78] is an important demographic construct that can provide an insightful explanation of consumers' online shopping behaviour at various stages of life. Previous studies showed that HLC has a significant moderating impact on adoption of technology.[17] Results from such studies will have the benefit of extending the current work to account for additional variance in online shopping behaviour.

Furthermore, it is important to recognize a critical limitation of this study. Data utilised in this study, whereas large and representative and with very low non-response rate were collected during the early stages of the diffusion of online shopping. As such, the online shoppers in this study are largely innovators. This may, to some extent, explain why some of our hypothesis particularly marital status, proficiency in English language, geographical remoteness, disability and access to motor vehicles were not supported. For example, we conceptualised that geographical remoteness effect is mediated by the word-of-mouth. However, the literature suggests that innovators are not impacted by the interpersonal channel of communications.[61] This also limits the generalisability of our findings to adopters other than innovators. More research is needed to test these hypotheses with data collected at later stages of the diffusion of online shopping. Another potentially fruitful area of research is to test the generalisability of the demographic models developed in this study in other socio-economic contexts, products and channels. In addition, this study only reflects the predictive power of demographics-based models at the category level adoption. It is plausible that prediction of sales at brand level is largely beyond the reach of demographics and better explained by other more theoretically rigorous or more behaviourally-driven models. More research is needed in this area.

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APPENDIX

Table A1: Definition and coding scheme of independent variables

Variable name	*Description*	*Codes*
Age	Age of respondents	0=18–19, 1=20–24, 2=25–29, 3=30–34, 4=35–39, 5=40–44, 45–49, 7=50–54, 8=55–59, 9=60–64, 10=65–69, 11=70–74, 12=75–79, 13=80+
Gender	Gender of the respondents	0=Women, 1=Men
Marital status	Registered marital status	0=Married/couple, 1=never married, 2=widowed, separated, divorced
Household size	Number of persons in household	1=one, 2=two, 3=three, 4=four, 5=five and above
Education	Level of highest non-school qualification	0=No non-school qualification, 1=Below bachelor degree, 2=Bachelor degree, 3=Above bachelor degree
Income	Personal gross weekly income in $	0=0–296, 1=297–424, 2=425–550, 3=551–681, 4=682–851, 5=852–1, 6=1114+
Occupation	Main occupation	0=Managers, professionals, associate professionals, advanced clerical workers, 1=Tradespersons and related, intermediate clerical, sales and service workers, intermediate production and transport workers, elementary clerical, sales and service workers, labours and related workers 2=no occupation
Country of birth	Country of birth	0=English-speaking countries 1=European except English-speaking countries 2=Southwest Asian and north Africa 3=South, East and Southeast Asia 4=Other
Language Skills	Proficiency in spoken English	0=Native speakers 1=Very well 2=Well 3=Not well/not well at all
Internet access	Respondents frequency of internet	0=No access, 1=less than one day a access at home in past 12 months, 2=1 day a month, 3=1 day fortnight, 4=1 day a week, 5=2 to 6 days a week, 6=7 days a week
E-banking	Whether financial services accessed Over the internet during past 3 months	0=No, 1=Yes
E-government		0=No, 1=Yes
E-share trading		0=No, 1=Yes
E-mail/chat	Use of e-mail or chat sites via the Internet in past 12 months	0=No, 1=Yes

Table A1 *continued*

Variable name	*Description*	*Codes*
Social activity	Number of social activity in past 3 months	0=0, 1=1, 2=2, 3=3, 4=4, 5=5, 6=6, 7=7, 8=8+
Disability	Disability or long-term health condition	0=Yes, 1=No
Face-to-face contact	Frequency of face to face contact with family or friends	1=Not recent contact, 2=Quarterly 3=Monthly, 4=Weekly
Remoteness	Geographical remoteness	1=Major cities, 2=Inner regional Australia, 3=Other areas
Motor vehicle	Access to motor vehicles	0=No, 1=Yes
Transportation	Perceived level of difficulty	1=Can easily get to the places with transport needed, 2=Sometimes have difficulty, 3=Often have difficulty, 4=Can't get to the places needed/never go out