The role of e-consumer empowerment on personal data disclosure in the digital economy

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ABSTRACT

Digital transformation has improved online shopping from the beginning of the 20th century. Online businesses have exponentially expanded the level of service delivery with the help of decision support systems using user digital footprint. E-consumer online behavioural data is progressively becoming a valuable asset for precise, granular online targeting. Consumers are being monitored to predict real-time demand based on browsing behavioural surplus. This paper assessed the influence of electronic consumer (e-consumer) empowerment on perceived trust, purchase intention, and the effects of data harvesting. A cross-sectional quantitative approach was used with an online survey of 400 respondents. Data was analysed using SPSS and R statistics with Structural equation modelling. The findings showed that electronic consumer empowerment influenced perceived trust, purchase intention, and the effects of data harvesting, which led to online self-disclosures used in real-time predictions. The results revealed that while some e-consumers were aware of free data exploitation, most e-consumers did not notice that their online data was being harvested and exploited by online retailers. This paper illuminated the role of e-consumer empowerment in optimising data harvesting to improve personalised customer service in the data-driven digital economy. These findings may assist digitalised companies to initiate loyalty programmes to compensate e-consumers for data resource input.

Keywords: digital transformation, online shopping, consumer behaviour, consumer data, data mining.

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1. INTRODUCTION

Digital transformation is becoming a managerial function in an exponentially growing data-driven digital economy. Society is intertwined with the internet, permitting digital citizenship, where participation is impossible without data sharing (Lutz, Hoffmann & Ranzini 2020). Contemporary capitalism requires online companies to be data-driven by accumulating e-consumer data to boost profitable strategies in the competitive digital economy (Sadowski 2019). The digital revolution is now extending to developing economies, where the technological renaissance is expanding in terms of materialism, unmasking beliefs, and personality traits (Mutsvairo, Ragnedda & Orgeret 2021). To compete favourably in a data-driven economy, digital marketers are now working with data scientists to unveil the hidden patterns of online shoppers. The theory of reasoned action (TRA) is crucial in explaining how online shoppers' beliefs influence online shopping decisions (Sharma 2019). Ghosal, Biswa, Prasad and Behera (2020) suggested that all theoretical influences on online consumer data disclosure are centred on the technology acceptance model (TAM), thereby compelling online shoppers to accept technology. Against this background, the empowerment of e-consumers is crucial in harnessing the harvesting of consumer data, which is raw material for decision-making in the growing data-driven digital economy. This paper assessed the influence of e-consumer empowerment on perceived trust, purchase intention, and the effects of data harvesting.

2. LITERATURE REVIEW

Online consumers are usually vulnerable to automated monitoring of browsing footprint — allowing online companies to use tag facilities that track, sort, and harvest e-consumer data using affiliated websites (Farman, Comello & Edwards 2020). Presently, free e-consumer data is a raw material used as a building block to generate revenue for capitalists, as neo-Marxist scholars critique the technological glorification, which has created inequalities between digital capitalists and society (Mutsvairo et al. 2021). Nevertheless, algorithm filtering and exploitation are pretentiously done to help online shoppers enjoy an easy shopping experience. Nevertheless, such unnoticeable operations may create discomfort during the online shopping journey (Lomborg & Kapsch 2020). Consumers have no intention of sharing their data while they are searching for products and services online. However, during their online engagements with retailers, their data is harvested freely and utilised in managerial decision-making processes. The mining of e-consumer data and the empowerment of e-consumers as providers of data requires additional attention and recognition. The literature review did not reveal any research that focussed on e-consumer empowerment concerning purchase intentions, perceived trust, and the effects of data harvest. E-consumer empowerment, the effects of data harvesting, perceived trust, and purchase intentions are discussed in the next subsections.

2.1 E-CONSUMER EMPOWERMENT

The economic value of e-consumer data has started a debate on the commodification of consumer data which is worth billions of dollars (Li, Liu & Motiwalla2021). E-consumer empowerment seeks to strengthen the relationship between online firms and e-consumers in a data-driven digital economy. Online companies deliberately use technology to attempt to mislead customers by popping up an illusion of control, to ensure security (Draper and Turow 2019). Based on recent studies, e-consumer data input has value to online companies. Therefore, if online shoppers are compensated for their data input, they tend to downplay the effects of self-disclosure due to the tendency that online companies have co-ownership rights to e-consumer data. However, auctioning data requires specific ownership to assign value depending on the willingness to exchange data for compensation (Li et al. 2021).

The growing need for digital transformation has compelled decision makers to focus on digital prowess with end-to-end integration of e-retailer Apps on smart devices of e-consumers, enabling real-time analytics using click, collect, and analyse systems (Bonnet & Westerman 2021). It is evident in the United States that individuals are willing to disclose their personal data in consideration of an economic return (Li et al. 2021). Empowering e-consumers can take various appropriate forms for fair treatment of consumers who provide data for decision making. Consumers whose online activities accumulate a valuable data reservoir always have little control and are often oblivious to the harvest of their data resources for profitable predictions. While consumers are leaving trails of browsing data on online shopping platforms, they remain unaware about the value of their self-disclosures.

2.2 EFFECTS OF DATA HARVEST

Data harvesting is associated with positive and negative effects. The negative effects posit a threat to online trader relations as consumers become savvier and more aware of the value of their data, exploited through data harvesting. However, the positive effects are that this improves consumer experience with increased personalisation, which, in turn, increases loyalty. Digital transformation has also ignited online surveillance activities that bring new consumer experiences (Lang, Xia & Liu 2021). With the surveillance of e-consumers, attractive opportunities often automatically appear in e-consumers' inboxes, like price specials that are allocated based on e-consumer profiles (Clarke 2019). Furthermore, tracking online shoppers’ browsing history provides information about hidden requirements of shoppers that necessitate personalised differentiated marketing practices which automatically match with consumer preferences (Bornschein, Schmidt & Mairer 2020). Machine learning technology classifies similar e-consumer behaviour patterns and movements to reproduce fine-grained behavioural segments with algorithms that automatically predict future possibilities for marketing strategy (Tong, Luo & Xu 2020). Although the positive effects of predicting consumer demand helps consumers to conveniently access goods and services online, online retailers accumulate enormous revenue from the same predictions. Since consumers are the providers of this useful data that has predictive power, they should be empowered for their contribution.

Moreover, public debates about e-consumer tracking are intensifying due to concerns about declining consumer autonomy escalated by data harvesting (Ruckenstein & Granroth 2019). However, Bornschein et al. (2020) argued that e-consumers have no power or choice in how websites automatically harvest their valuable data while transacting online. Clarke (2019) recommended that the threat of surveillance should be beyond reproach, to avoid the engendering of fear towards the controlling of consumer power through screening behavioural patterns. Kendell (2020) warned that behavioural manipulation deprives e-consumers of choice by influencing purchase intentions towards retailers’ product offerings, thereby diminishing consumers’ rational behaviour. There is a dearth of research with respect to empowering e-consumers in consideration of the effects of data harvesting. Also, due to the positive effects related to customisation, consumers develop trust which ultimately exposes them to data exploitation.

2.3 PERCEIVED TRUST

Online shoppers face a dilemma of trust issues, seeking enormous amounts of choice-related information from different companies for better decision-making, leading to the harvesting of browsing footprints (Kumar, Rajan, Venkatesan & Lecinski 2019). Perceived trust is the probability that e-consumers believe in the legitimacy of online companies (Carstens, Ungerer & Human 2019). Bornschein et al. (2020) argued that positive perceived trust owing to brand popularity lures e-consumers to deliberately accept tracking. Trust is an antecedent of perceived risk, allowing for a mental guarantee towards risk-free online shopping (Kaur & Arora 2020). Furthermore, the interlinking of social platforms with e-tailing websites is propelling effective data sharing that boosts online shopping’s perceived trust. This carelessly results in e-consumers revealing free behavioural data that is exploited by e-retailers without the e-consumer's knowledge (Bugshan & Attar 2020). E-consumers are ignorantly succumbing to data disclosure in consideration of positive expectations from the offerings of the online retailer. Since trusting consumers are willing to provide valuable insights that are profitably used by online companies, they should be empowered in a bid to provide unlimited data resources used in decision making.

Furthermore, due to digital marketing activities that are focusing on trending content on online platforms, successful marketers provide popular brands that attract e-consumers' unforeseen free data exploitation through online engagements motived by trust (Geric & Dobrinic 2020). Purchase and Volery (2020) agreed that innovation enhances product visibility, credibility and novelty, and ultimately brand popularity with curiosity-driven online searches for upgrades, which inadvertently expose e-consumers to free data exploitation. Brand popularity lures e-consumers to confidently reveal behavioural data due to perceived trust, leading to free data exploitation. Therefore, once e-consumers are empowered with control, they tend to engage online with confidence, which increases the pull of browsing data harvested for real-time decision-making and targeting. Recent studies show no research on the role of e-consumer empowerment in influencing perceived trust in facilitating data harvest. Once perceived trust is positive, e-consumers develop purchase intentions.

2.4 PURCHASE INTENTION

Hamouda (2021) defined purchase intention as the possibility of a shopping action after evaluating alternatives. Choi and Park (2021) stated that the TAM activates subjective reasoning to transact online, thereby exposing unsuspecting consumers to data harvesting. Lomborg and Kapsch (2020) believed that personalised algorithms shaping purchase intention normally go unnoticed by online shoppers. Furthermore, purchase convenience (because of TAM) about the ease of technology alongside its usefulness, triggers online purchase willingness leading to data harvesting (Baeshen 2021). The predictions of product need recommended by algorithms present a pleasant behavioural monitoring experience (Mican, Sitar-Taut & Moisescu 2020). During online information searches, companies' algorithms distinguish utilitarian motives from hedonic motives, reducing information overload by upscaling choices based on search criteria (Nam & Kannan 2020). Once the benefits of online shopping exceed the risks involved, shoppers downplay the risks, embarking on purchase intentions linked to self-disclosure (Feher 2021). In the data-driven economy, e-consumers disclose data even without requests, owing to the influence of the benefits expected. Therefore, trust has an influence on purchase intention which prompts online shoppers to engage online, leaving a trail of browsing behavioural data available for exploitation by online companies. Notably, the empowerment of e-consumers with secure user-friendly technology and valuing their data input can boost online purchase intentions and enable search behaviour harvesting used to make accurate profitable decisions.

Furthermore, real-time communication influences purchase intentions as online shoppers unwittingly fall prey to e-retailers who monitor their behavioural intentions for targeting (Grewal, Gauri, Roggeveen & Seturaman 2021). Real-time communication increases the willingness to develop purchase intentions, allowing for the monitoring of online behavioural intentions for targeting. Therefore, convenience encourages the probability of self- disclosure as online shoppers become more familiar and develop the trust to freely register online in anticipation of actually making a purchase, thereby allowing the process to expose shoppers to free data resource exploitation without realising. Hidden algorithms connected to recommender systems filter the browsing behaviour and match products to e-consumers' preferences, increase consumer convenience and therefore enhancing their willingness to disclose data.

3. RESEARCH METHODS

The study used a quantitative research design method. The online survey questionnaire was analysed using SPSS and R statistics. The population for this cross-sectional study consisted of 400 online shoppers from Durban, KwaZulu-Natal, South Africa. Quota sampling was used under convenience settings based on attributes of key categorical variables of the population. System frequencies, to sample every nth visitor to the website, were incorporated in the internet protocol addresses (IP) allowing specific sub-sets of visitors and restricting multiple submissions (Fricker 2017).

Pretesting with 42 online shoppers in Durban was conducted to ensure the reliability of the measuring tool before conducting the full-scale survey. The assessment of a measurement model was conducted by testing reliability and validity. In structural equation modelling (SEM), exploratory factor analysis (EFA) was used owing to little information about the expected latent structure for observed indicators (Finch 2020).

4. RESULTS AND DISCUSSION

Nine demographic variables were considered for the survey. The dimensions are summarised below:

Forty-four percent of respondents reported that they shop monthly. In response to gender, a score of 65.2% of online shoppers were male. However, existing literature revealed that females are more likely to carry out online shopping than males (Lipschultz 2020). Fifty-two percent of online shoppers were employed full-time and could afford online shopping using their bank card details. Almost half of the online shoppers were in their youth. The race variable is mainly represented by 62.8% Black respondents. Within the marital status category, 68.2% of the respondents claimed to be single. This indicated that single individuals shop online more frequently than other groups in this category. In the education category, 68.2% of the respondents claimed be in possession of tertiary qualifications. All of the above-mentioned respondents are in the circle of online shoppers, and are therefore exposed to data harvesting, making them vulnerable. After analysing categorical variables, exploratory factor analysis was conducted for continuous variables.

4.1 EXPLORATORY FACTOR ANALYSIS (EFA)

Validity testing uses either EFA or confirmatory factor analysis (CFA) but not both. This is because EFA and CFA are opposite on the continuum and must never be used in the same study (Finch 2020). The questionnaire used is new and the volatility is due to the dynamics of the digital phenomenon in this study, therefore an EFA is suitable to ensure validity. Ensuring the appropriateness of factor analysis requires the Kaiser-Meyer Okin (KMO) sampling adequacy to be ≥ 0.6 and a p-value at $p \leq 0.01$ level of significance (Dawson 2018). Factor analysis allows the reduction of dimensions by retaining variables with an eigenvalue of 1, thereby extracting uncorrelated factors (orthogonal) (Finch 2020). Table 1 shows the sample adequacy tests.

TABLE 1. SAMPLE ADEQUACY TESTS

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.904
Bartlett's Test of Sphericity	Approx. Chi-Square	5654.596
	df	666
	Sig.	.000

As reflected in Table 1, the KMO is 0.9 which indicates sample adequacy, and the p-value is significant at 0.00. Table 2 shows the factors extracted from factor analysis tests.

Table 2 reflects that the Eigenvalue of the first factor is 9.593, which reduces as more factors are added, with the 8th factor contributing 1.087 of the eigenvalues, making the 8th factor the cut-off baseline. However, only four factors were considered for the study, as indicated in Table 3.

TABLE 2. PRINCIPAL AXIS FACTORING

Factor	*Initial Eigenvalues*		
	Total	% of Variance	Cumulative %
1	9.593	25.928	25.928
2	3.445	9.310	9.310
3	2.008	35.238	35.238
4	1.664	5.426	5.426
5	1.244	40.665	40.665
6	1.164	4.497	4.497
7	1.133	45.162	45.162
8	1.087	3.361	3.361

The factor analysis grouped items (see Table 3) and the results of the EFA were used to conduct the SEM. The reliability test results of the four factors (Effects, Perceived trust, Purchase intention and E-consumer empowerment) considered in the study were good. An alpha of 0.70 is okay and 0.60 for a new scale is good (Rouf & Akhtaruddin 2018).

Participants were asked to respond to the statements according to the Likert scale of strongly disagree to strongly agree. The following scores were obtained:

4.1.1 Effects

Eighty-one percent of respondents agreed that their information is helpful to online companies, which suggests that online companies use e-consumer data for economic benefits without rewarding the owners of the data input. Rust (2020) shared that e-consumer data is useful for informed decision-making. When respondents were asked whether their data was used to target them, 65% agreed, while 60% agreed that their data was profitable for company predictions. Therefore, empowering e-consumers with rewards for their data input can boost online shopping, by supporting browsing data harvesting for targeted predictions.

4.1.2 Perceived trust

Eighty-nine percent of respondents buy from credible websites. Bornschein et al. (2020) affirmed that e-consumers choose to shop from credible websites. A similar result was obtained when respondents were asked whether they buy from credible websites and recommended online companies. Respondents also considered protection, in that 86.25% of respondents agreed that they bought from companies that protected their privacy. Results showed that 75.25% of respondents were happy with online customer care. Overall, the empowerment of e-consumers through customer care and security builds trust, enhancing online data harvesting for real-time decisions as e-consumers continue to engage online.

4.1.3 Purchase intention

Ninety percent of the respondents considered convenience in on-line shopping, not realising that behind the scenes, online companies were tracking their valuable data. Certainly, purchase convenience because of the ease of technology motivates online purchases leading to data harvesting (Baeshen 2021). The factor, online shopping satisfies my preferences, scored 80.25%. However, once their preferences were met, they downplayed free data resource harvesting, which benefits online companies more than e-consumer satisfaction does, which comes at a cost. Nevertheless, 87.75 of respondents were happy with online shopping. It is noteworthy that the empowerment of e-consumers by acknowledging their data input could further enhance online shopping, boosting revenue because of continued purchase intentions.

4.1.4 E-consumer empowerment

Eighty-five percent of respondents agreed that their online data is valuable to online companies. Li et al. (2021) agreed that the economic value of e-consumer data is billions of dollars. Fifth-five percent of respondents agreed that they should have control over their data, which is controlled by online firms to make profitable predictions. Bornschein et al. (2020) concurred that e-consumers are powerless and have no control over their data as they shop online. Furthermore, 78% of respondents agreed that online companies are harvesting their data which may cause consumer defections. However, the empowerment of e-consumers by recognising the value of their data and securing their online transaction can motivate trust and boost online shopping. After analysing the descriptive statistics, SEM was used to conduct inferential statistics.

TABLE 3. FACTOR ANALYSIS TESTS

Effects
EF1. I recommend dependable online companies to my peers
EF2. We provide our free information, which is used for profitable predictions by online companies.
EF3. Our previous online records are used by online companies to target us
EF4. Disclosing our information during online shopping is inevitable

Perceived trust
PT1. I buy from recommended online companies
PT2. I buy from online companies that protect my privacy
PT3. I shop from credible online websites
PT4. Online shopping saves time
PT5. I only disclose my information to online companies that deserve my loyalty
PT6. I am happy with online customer care
PT7. I regard trust when disclosing my information during online shopping
PT8. I consider price when shopping online
PT9. Online feedback helps to make informed shopping decisions
PT10. I always buy from online companies with quality services
Purchase intention
PI1. I am happy with online shopping
PI2. I consider reputable online companies when shopping online
PI3. Online shopping satisfies my preferences
PI4. Online shopping is convenient
PI5. I benefit from shopping online
E-consumer empowerment
EE1. Our online information is collected by online companies
EE2. We should have control over our online information
EE3. Our online information has value to online companies
EE4. We should be paid by online companies using our information

4.2 STRUCTURAL EQUATION MODELLING

Tan-lei and Lin (2018) propounded that covariance structures with SEM allowed for analysis of moment structures. Factor loading is the measure of the relationship between each latent variable and the observed indicator, where the unique variances are parts of the indicator that are not concomitant to the observed variable (Finch 2020). Correlation and covariance tests were conducted using SEM. The results are indicated in the next subsections. Figure 1 represents the measurement model which focuses on the correlation estimates.

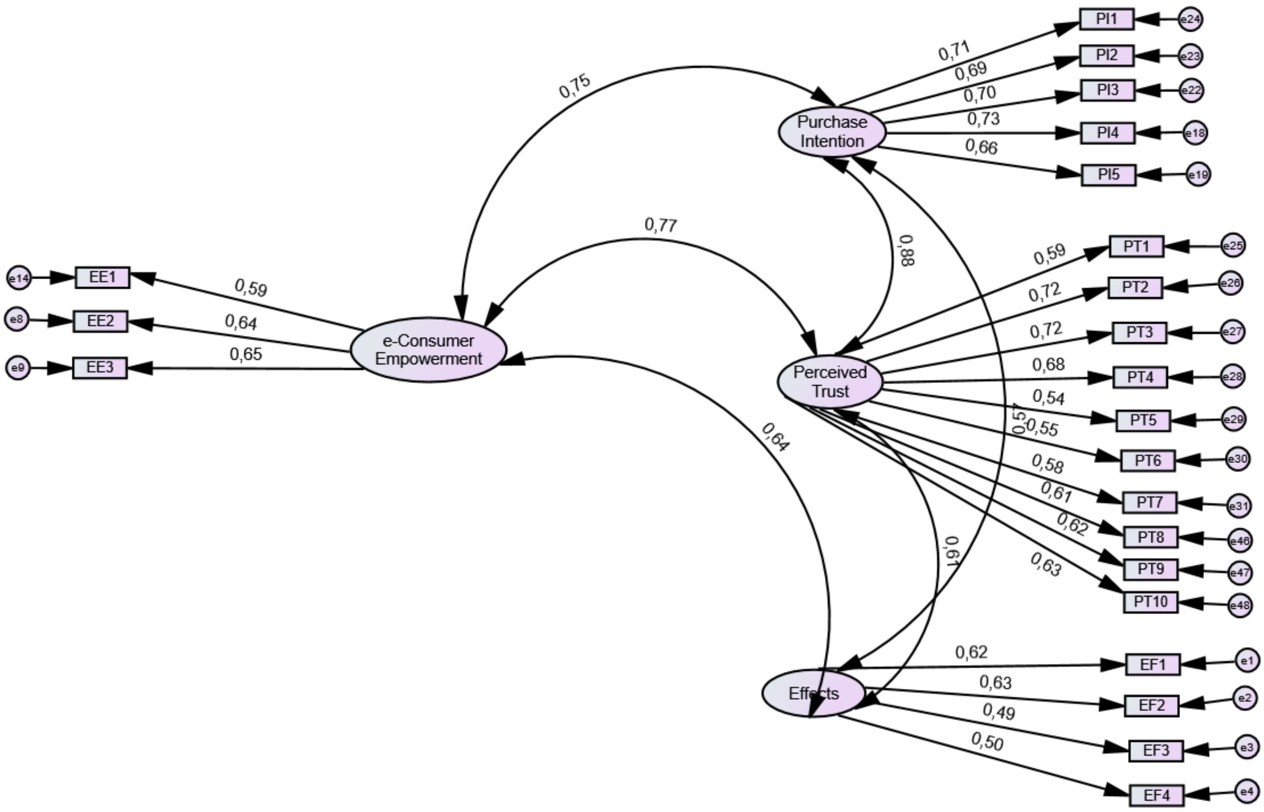

FIGURE 1. CORRELATION STRUCTURE

Figure 1 indicates the relationships between the variables. Correlation coefficient values were extracted from Figure 1 and are summarised in Table 4.

TABLE 4. CORRELATION ESTIMATES

			Estimate
EE	<->	PI	0.746
EE	<->	PT	0.770
EE	<->	EF	0.638
PI	<->	PT	0.879
PI	<->	EF	0.567
EF	<->	PT	0.613

As reflected in Table 4, the relationship between variables are positive. For example, e-consumer empowerment (EE) has a positive relationship with purchase intention (PI) with a score of 0.746, which indicates that the more e-consumers are empowered, the more the purchase intention or vice versa. Empowerment of e-consumers can intensify online purchase intention leading to online engagements that are harvested for future targeting. E-consumer empowerment (EE) and perceived trust (PT) are also positively related, as reflected in Table 4, with a score of 0.770.

The greater the empowerment of e-consumers, the more perceived trust propels online shopping, leading to an increase in e-consumer data harvesting. Furthermore, the relationship between e-consumer empowerment (EE) and the effects (EF) of data harvesting has a score of 0.638, which implies that the more e-consumers are empowered, the greater the effects of data harvesting or vice versa. A score of 0.879 concerning the relationship between purchase intention (PI) and perceived trust means that trust influences purchase intentions that can be converted to online purchases, leading to online engagements that are harvested by online companies. Purchase intention (PI) and effects (EF) have a moderate relationship at 0.567, while effects (EF) and perceived trust (PT) have a score of 0.613 which indicates e-consumer increased trust because of the effects of data harvesting. Table 5 shows the model fit indices extracted from the results of SEM.

Table 5 reflects a CMIN/DF of 3.14, which is rounded off to 3, the comparative fit index CFI of 0.86, which is rounded off to 0.9, and the RMSEA, which is 0.73. Model assessment using the goodness-of-fit indices is a process for interpreting the outcome of SEM where CFI and the Tucker-Lewis index (TLI) with values ≥ 0.90 show good fit, CMIN ≤3.0 is a good fit, and the RMSEA which is the root-mean-square error of approximation ≤0.08 but >5 is also a good fit (Olugboyega & Windapo 2022; Tan-lei & Lin 2018). Therefore, based on the indices in Table 5, the model fits the data, Figure 2 represents the structural model.

TABLE 5. MODEL FIT INDICES

Model	NPAR	CMIN	DF	P	CMIN/DF
Default model	68	650.277	207	.000	3.141
Saturated model	275	.000	0		
Independence model	44	3449.922	231	.000	14.935
Model	**NFI Delta1**	**RFI rho1**	**IFI Delta2**	**TLI rho2**	**CFI**
Default model	.812	.790	.863	.846	.862
Saturated model	1.000		1.000		1.000
Independence model	.000	.000	.000	.000	.000
	PRATIO	**PNFI**	**PCFI**		
Default model	.896	.727	.773		
Saturated model	.000	.000	.000		
Independence model	1.000	.000	.000		
	NCP	**LO 90**	**HI 90**		
Default model	443.277	370.121	524.044		
Saturated model	.000	.000	.000		
Independence model	3218.922	3032.555	3412.616		

Model	**RMSEA**	**LO 90**	**HI 90**	**PCLOSE**
Default model	.073	.067	.080	.000
Independence model	.187	.181	.192	.000
Model	**FMIN**	**F0**	**LO 90**	**HI 90**
Default model	1.630	1.111	.928	1.313
Saturated model	.000	.000	.000	.000
Independence model	8.646	8.067	7.600	8.553
Model	**AIC**	**BCC**	**BIC**	
Default model	786.277	794.596		
Saturated model	550.000	583.644		
Independence model	3537.922	3543.305		
Model	**ECVI**	**LO 90**	**HI 90**	**MECVI**
Default model	1.971	1.787	2.173	1.991
Saturated model	1.378	1.378	1.378	1.463
Independence model	8.867	8.400	9.352	8.880
Model	**HOELTER .05**	**HOELTER .01**		
Default model	149	158		
Independence model	31	33		

Based on the factor loadings in Figure 2, the following hypotheses were generated after conducting the path analyses.

Hypotheses

H_1. E-consumer empowerment has a positive influence on perceived trust

H_2. E-consumer empowerment has a positive influence on purchase intention

H_3. E-consumer empowerment has a positive influence on the effects of data harvesting

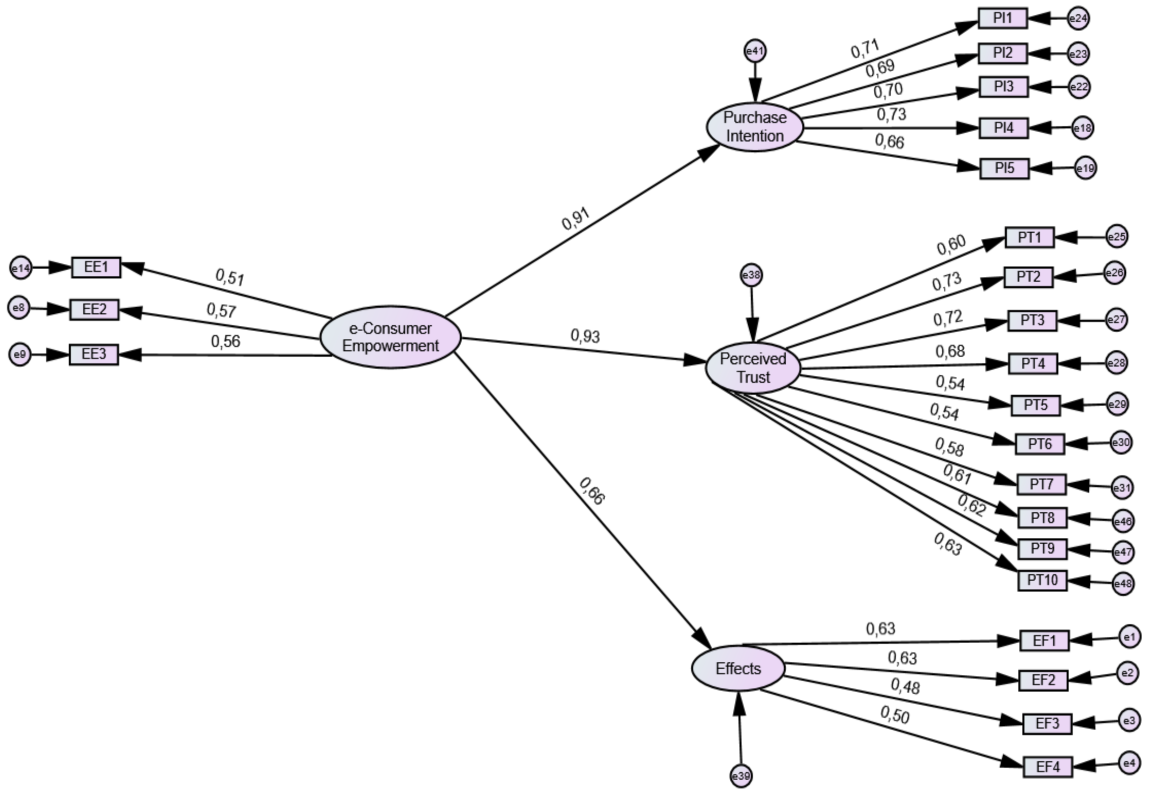

FIGURE 2: PATH ANALYSES

5. DISCUSSION

As reflected in Figure 2, e-consumer empowerment positively influences perceived trust with all factor loadings over 0.5 and β=0.93 meaning that there is a 93% possibility that e-consumer empowerment influences perceived trust. The empowerment of e-consumers motivates e-consumers to shop online with confidence. Once e-consumers develop trust, they transact online, providing data insights that are harvested by online companies for customisation and personalisation based on browsing behaviour. Bornschein et al. (2020) also affirmed that positively perceived trust lures e-consumers to deliberately accept tracking. Furthermore, Figure 2 reflects that e-consumer empowerment positively controls purchase intention with all factor loading >0.5 and β=0.91, which implies that there is a 91% probability that e-consumer empowerment influences purchase intention. Therefore, if e-consumers are empowered, they develop purchase intention by searching for products on online websites, leaving a trail of valuable data that is harvested for profitable precise targeting.

Real-time communication increases the willingness to develop purchase intentions, allowing for the monitoring of behavioural intentions online for targeting (Grewal et al. 2021). E-consumers empowered with real-time communication about the value of their data will easily develop online purchase intentions in anticipation of gaining from the value of their data input. Figure 2 shows that there is a positive influence of e-consumer empowerment on the effects of data harvesting with only one-factor loading <0.5 while other factor loadings >0.5 and β=0.66 so there is a 66% likelihood that the empowerment of e-consumers can positively propel of data harvesting. Harvesting data requires specific ownership to assign value depending on the willingness to exchange data for compensation (Li et al. 2021). So, if e-consumers are empowered, they can be willing to accept data harvesting effects. Therefore, as the digital environment is developing, online shoppers are becoming savvy about online data value to online firms, but they are not rewarded for the production of the valuable data input.

The majority of the respondents agreed that they should have control over their online data. So, e-consumers should be empowered on online platforms so that their data is valued, thereby developing trust and leading to purchase intention. However, more emphasis is vested on harvesting as much free data as possible from e-consumers. Online traders use sophisticated technology to monitor e-consumer data resources to predict and target online shoppers based on their browsing behavioural history. The intention to purchase online involves shoppers searching online for clues about the product, leaving valuable browsing data harvested for precise predictions. To beat competition in the digital data-driven economy, managers use e-consumer data to make real-time decisions to keep pace with the dynamics of a volatile online landscape. However, this paper shows that e-consumers are progressively becoming enraged by the harvesting of their data. As e-consumers become exponentially aggravated with data harvesting, there is a possibility of defection from online shopping because of the negative effects of data harvesting.

E-consumer empowerment has a positive relationship with the effects of data harvesting, which can boost the business. Therefore, the more managers empower e-consumers, the more they gain trust and willingness to accept data harvesting. Since online trade depends on e-consumer data, optimising data requires managers to seek empowerment strategies that can generate rich data from e-consumers. E-consumer data should be assigned its economic value by intensifying e-consumer empowerment through equivalent rewards to acknowledge e-consumer data input just like any other raw material valued for business.

6. CONCLUSION

The purpose of the paper was to assess the influence of e-consumer empowerment on the effects of data harvesting, perceived trust, and purchase intention. The findings indicate that there is a positive influence of e-consumer empowerment on the effects of data harvesting, perceived trust and purchase intention. E-consumers trust online shopping once they are empowered to provide valuable data input which is used for predictions and personalised online services. As online shoppers gain trust, they develop purchase intentions that involve information search. During the e-consumer shopping journey, the browsing of information on the online platform provides enormous search behavioural data which is harvested by online companies for real-time decision support. Therefore, empowering e-consumers using various strategies involving the acknowledgement of the value of e-consumer data input and security motivates trust which in turn triggers purchase intention. Ultimately the effects of data harvesting are downplayed rendering online companies to optimise e-consumer data harvest which has become a necessary activity in the growing digital data-driven economy embracing digital transformation and stiff digital competition.

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