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A FRAMEWORK TO SUSTAIN IMPACT TECHNOLOGY STARTUPS IN SOUTH AFRICA

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Abstract

The study employs the Technology-Organisation-Environment (TOE) model to develop a framework for adopting marketing automation tools by South African Impact Technology Startups (ITSs). This involved critically analysing the relationships between Awareness of marketing automation tools (AMAT) and the sustainability (SS) of ITSs. It also involved examining the relationship between the various factors of the TOE framework and AMAT and the mediating influence of AMAT in the relationship between the TOE framework factors and SS.

This study employed a quantitative exploratory research design and was conducted in Johannesburg, Pretoria, Durban, Cape Town, and Mafikeng. Structural Equation Modeling (SEM) was used to test the various hypothesized relationships.

The research revealed that Awareness of marketing automation tools has a direct positive relationship with the factors of the TOE framework and with the sustainability of ITSs. It also became evident that understanding marketing automation tools acts as a mediator in the indirect link between the TOE framework and the sustainability of ITSs.The findings of this study will pave the way for a deeper understanding of the role that marketing automation can play in the sustainability of ITSs.

Keywords

Marketing Automation, Digital Marketing, Impact Tech Startups, Technology, Organisation, Environment, Sustainability

Introduction

According to Seo and Lee (2019, p.2), a technology 'startup' is a temporary, early-stage, knowledge-creation organisation highly reliant on technology and innovation. Chammassian and Sabatier (2020) argue that "technology startups have been a bulwark of business model innovation, the commercialisation of innovation, employment creation and economic growth." Several researchers (Skawinska and Zalewski, 2020; Gidron et al., 2021; Telukdarie et al., 2022), as cited in Muathe and Otieno (2022:23), argue that governments rely on startups to innovate, create jobs and drive economic growth. Vadera (2019), as cited in Swartz et al. (2022), states that values-driven tech startups are central to the sustainable development of emerging markets.

Tech Startups that focus on addressing the Sustainable Development Goals (SDGs) are known as ITSs or Impact Tech Startups (Skala, 2022). Gidron et al. (2021, p.1) opine that the role of ITSs in addressing the SDGs has been acknowledged by the United Nations Interagency Task Team (IATT) on Science, Technology and Innovation for SDGs. This is because of a growing realisation that "the world's future threatens to be bleak if it continues to pursue profit maximising, neo-liberal economic policies without regard to the effect on health, social inequalities, and the environment" (Gidron et al., 2021, p.1). The researchers above also argue that ITSs and social enterprises face two main challenges: sustainability and scalability.

Against the above background, this study will explore how marketing automation can contribute towards the long-term sustainability of ITS and develop a framework to maximise the value of ITSs in South Africa.

Literature Review

Digital marketing has led to a proliferation of media touchpoints and increased the number of advertising messages consumers receive daily. Marketing automation can help marketers process large amounts of data gathered while targeting customers (Mannel, 2019). Mhlongo et al. (2024, p.1365) argue that social media platforms have improved the visibility of startups. "Entrepreneurs can leverage platforms like Instagram, Facebook and Twitter to create an online presence, engage with potential customers, and showcase their products or services" These authors further state that Search Engine Optimisation (SEO) techniques make startups easily discoverable on search engines. According to Patil et al. (2022) and Chakraborti et al. (2022), digital marketing is critical to the success of tech startups because it helps them achieve meaningful customer engagement at a low cost. Digital marketing is more affordable and delivers better Return on Investment (ROI) than traditional advertising (Pandey and Tilak, 2022).

Despite the importance of digital marketing to tech startups, the adoption of digital marketing by startups remains low (Otika et al., 2022). Suharno et al. (2020) and Wamba-Taguimdje et al. (2020), as cited in Alexandro and Basrowi (2024, p.139) assert that "the capability of information technology to increase the efficiency and effectiveness of business processes in an organisation is a tool for accelerating the organisation's steps towards a smart digital organisation as a digital agency." Unfortunately, Ritze et al. (2019) as cited in El-Shihy and Mohamed (2023, p.91) argue that some startup owners "doubt whether such technologies will yield the returns promised by the advertisers."

Patil et al. (2022), as cited in El-Shihy and Mohamed (2023, p.91), argue that "digital marketing adoption (DMA) is vital for the success of startups. Direct marketing (DM) channels help startups construct their brand image and develop strong relationships with their audience by forming strong bonds with members of online communities and giving constant updates on their business activities at low cost." However, according to Chakraborti et al. (2022) as cited in El-Shihy and Mohamed (2023, p.91) "small businesses (especially impact tech startups) are not adopting digital marketing the same ways as well-established companies. They are unaware of their potential benefits."

Mannel and Engelen (2019, p.4) opine that "marketing automation bridges the gap between individual targeting and efficient marketing actions. Jarvinen and Taiminen (2016), as cited in Mattos, Casais and Braga (2021, p.90), define marketing automation as "a platform that facilitates, automates, and measures marketing tasks and workflows, such as email marketing, landing pages, website, social networks, text messages and YouTube." According to Hammoud et al. (2022), marketing automation "has many features, including email marketing, marketing databases and analytics.

Mannel and Engelen (2019, p.3) argue that due to advances in technology, a proliferation of brands and fragmentation of the media landscape, consumers are inundated with an abundance of marketing messages, making it difficult for brands to stand out. For startups to stand out when targeting consumers, "this overwhelming amount of data which can be gathered along the purchase funnel has to be managed more efficiently, and marketing automation is one solution to handle the mass information" (Mannel and Engelen, 2019, p.3).

Nath (2017), as cited in Hammoud et al. (2022), argues that "marketing automation can be a small business's best solution, handling tasks and developing insights that smaller organisations just do not have the human resources to tackle as well as the ability to grow the business, without increasing their budget." Amini and Javid (2023, p.1221) argue that "according to TOE, technologies that are currently in use by the firm and technologies, which are in the market but not in use by the firm, influence the adoption decision." According to Ahmad, Ahmad and Abu Baker (2018) and Matsumoto and Onuma (2020), as cited in Putro and Takahashi (2024, p.2), "previous studies have highlighted the importance of recognising the potential benefits of new technologies to improve their adoption and use."Doyle (2000), as cited in Murphy (2018, p.6), "organisational efficiency is a driver for investing in a marketing automation platform."

In light of the above, there is a need to explore how ITS's Awareness of the advantages of marketing automation tools impacts their adoption of these tools, which could result in their sustainability.

According to Samat, Yusoff, Anual and Mohamad (2023, p.226), "Organisational support such as financial resources gauges the company's capital accessible for creating and keeping up the social media marketing venture." Hasani and O'Reilly (2021), as cited in El-Shihy and Mohamed (2023, p.95), define financial support as a "startup's capital originating from various resources as owners, friends, families, and other externalities, such as financial grants and bank loans."

Dholakia and Kshetri (2004), as cited in Samat et al. (2023, p.226), argue that "previous researchers have proven that the size of the company and the limitation of its financial resources are determinants in adopting social media marketing to improve a company's performance." Several other researchers (Davcik and Sharma (2016), Baidoun et al. (2018) and Ahmad et al. (2017), as cited in El-Shihy and Mahomed (2023, p.95) concur with the above findings. To further examine the relationship between financial support and technology adoption by ITSs in South Africa, it is postulated that the availability of financial support positively impacts ITS adoption of marketing automation tools.

According to El-Shihy and Mohamed (2023, p.109), the adoption of digital marketing significantly impacts the performance of startups. El-Shihy and Mohamed (2023, p.109) further reported that a study by Tornikoski and Newell (2105) found that "digital marketing adoption positively affects SME's performance." Iit is postulated that the adoption of marketing automation positively impacts the sustainability of ITSs.

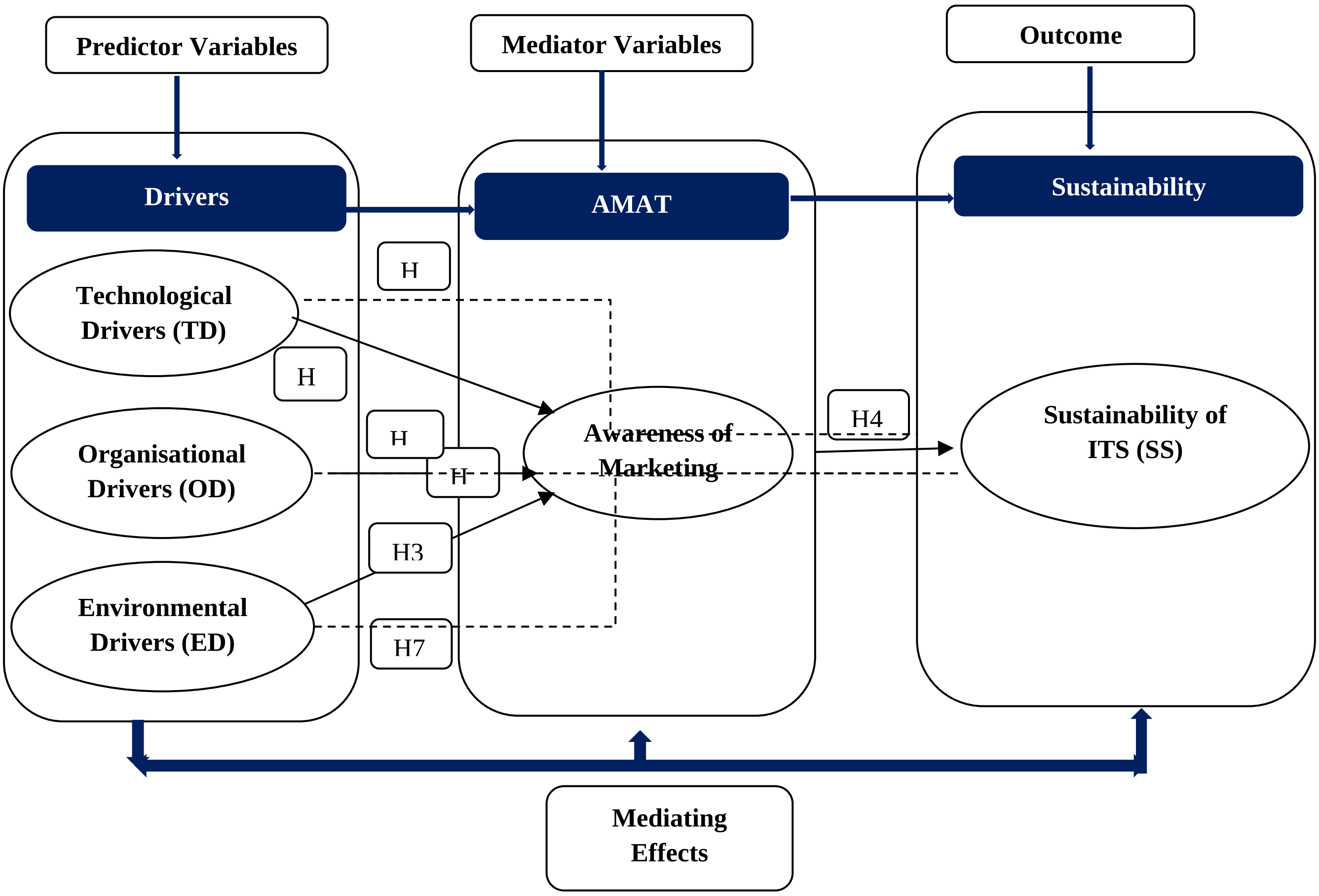

Figure 1: Proposed Conceptual Model

Research Methodology

A quantitative study was conducted using a self-administered questionnaire to survey a sample of 217 Impact Tech Startup owner-managers from a population of 450 ITSs in food security, employment services, fintech, edutech, agritech, and the green economy, amongst others (Taherdoost, 2017, p.237). Structural equation modelling (SEM) was conducted since Henseler and Sarstedt (2013), as cited in Muramalla and Muramalla (2019, p.365), stated that "data analysed through PLS-SEM is the most prominent technique to get results from surveyed data." SEM is comparable to regression analysis but is more robust because it evaluates the causal relationship between constructs while simultaneously controlling for measurement error (Sartedt, Ringle, Smith, Reams & Hair 2014). SEM is a structure that incorporates the simultaneous solution of systems of linear equations and procedures such as regression, factor analysis, and path analysis (Harrell, 2015). Concurrent Confirmatory Factor Analysis (CFA) and Path Analysis were performed with Smart PLS (Davari & Rezazadeh, 2015). CFA assesses how well the latent variables are measured by the observed variables (Li, 2016). In contrast, the purpose of path analysis is to examine causal relationships among unobserved variables (Mueser et al., 2017).

Research Findings

The study was conducted via a survey of 217 impact tech startups; the response rate was 67% since 146 usable questionnaires were completed. According to the findings, 54.1% of the respondents were male, and 45.2% were female. The 20–30 age group constituted the most significant proportion of respondents, at 52.7%, followed by 32.9% of respondents in the 31–40 age group.

The data also revealed that 36.3% of the participants possessed a postgraduate qualification. The next significant category consisted of individuals with undergraduate certificates, comprising 33.6% of the respondents.

Geographically, provincial representation is dominated by Gauteng (56.8%), which is known as a hub for economic and technological activity, suggesting more significant exposure to digital marketing innovations. The Western Cape was also highly represented (28.1%), reflecting its role as a centre for entrepreneurship. The Northwest comprised 13% and KwaZulu-Natal a mere 2.1%.

In terms of the level of seniority of participants from the various startups, junior managers were highly represented (32.2%), closely followed by those at the middle level at 29.5%. Participants in executive-level positions constituted 26.7%, while seniors garnered a share of 6,08%.

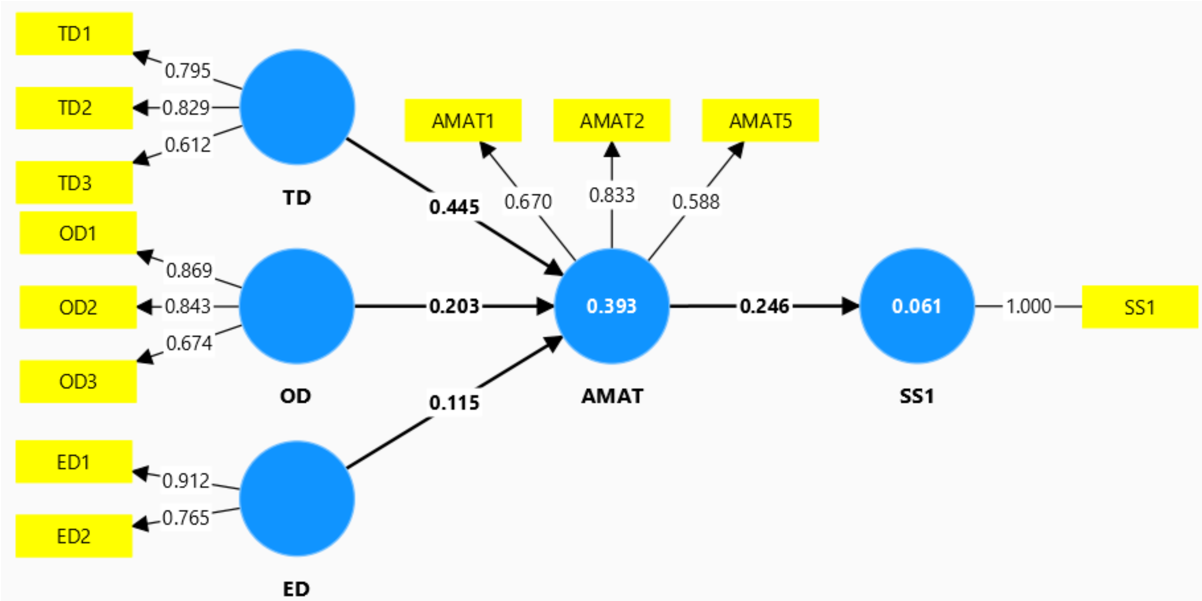

Figure 2: Research Model

Note: AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'

Factor Loadings

Factor loading refers to "the extent to which each of the items in the correlation matrix correlates with the given principal component. Factor loadings can range from -1.0 to +10, with the highest absolute values indicating a higher correlation of the item with the understanding factors" Pett et al., 2003; Sarstedt et al., 2014). Some of the items in the study have factor loadings less than the recommended value of 0.50 (Melkamu, Gelaye, Matebe, Lindgren, and Erlandsson, 2022). Hence, some items were removed, as presented in Table 1.

	AMAT	ED	OD	SS	TD
AMAT1	0.670				
AMAT2	0.833				
AMAT5	0.588				
ED1		0.912			
ED2		0.765			
OD1			0.869		
OD2			0.843		
OD3			0.674		
SS1				1.000	
TD1					0.795
TD2					0.829
TD3					0.612

Table 1: Factor Loadings

Note: AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'

Variance Inflation Factors (VIF) statistics assess multi-collinearity in the indicators (Fornell & Bookstein, 1982). According to Hair et al. (2016) and Venkatesh and Parimalarenganayaki (2023), multi-collinearity is not a serious issue if the value for VIF is below 5. Table 2 presents the VIF values for the indicators in the study and reveals that the VIF for each indicator is below the recommended threshold.

	VIF
AMAT1	1.108
AMAT2	1.184
AMAT5	1.092
ED1	1.230
ED2	1.230
OD1	1.417
OD2	1.602
OD3	1.426
SS1	1.000
TD1	1.271
TD2	1.411
TD3	1.161

Table 2: Multi-collinearity Statistics (VIF) for indicators

Note: AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'

Reliability Assessment

The most used methods for establishing reliability include Cronbach's Alpha and Composite Reliability (CR). The results for both Cronbach's Alpha and Composite Reliability results are presented in Table 3. The Cronbach's Alpha ranged from 0.702 to 0.938, whereas Composite Reliability statistics ranged from 0.809 to 0.947. Both reliability indicators have reliability statistics over the required threshold of 0.70. Hence, construct reliability was established.

	Cronbach's alpha	Composite reliability (rho_c)	Average variance extracted (AVE)
AMAT	0.492	0.743	0.496
ED	0.604	0.828	0.708
OD	0.737	0.840	0.640
TD	0.612	0.793	0.565

Table 3: Construct Reliability Analysis

Note: AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'

Construct Validity

Statistically, using PLS-SEM, construct validity is established when there is convergent validity and discriminant validity. Table 4 shows the AVE value for each of the constructs. The convergent validity results based on the AVE statistics in the current study show that all the constructs were greater than the recommended value of 0.50 (Melkamu, Gelaye, Matebe, Lindgren, and Erlandsson, 2022). However, the CR when all the constructs were greater than .70. Hence, convergent validity is not an issue.

Research construct	Average variance extracted (AVE)
AMAT	0.500
ED	0.708
OD	0.640
TD	0.565

Table 4: Construct Convergent Validity (AVE)

Note: AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'

Discriminant validity is the degree to which measures of different concepts are distinct. If two or more concepts are unique, then valid measures of each should not correlate too highly (Carlson and Herdman, 2012). In this study, the square root of AVE (in Bold and Italics) for a construct was greater than its correlation with another construct (Table 5). Hence, it provides strong support for the establishment of discriminant validity.

	AMAT	ED	OD	SS1	TD
AMAT	***0.704***				
ED	0.290	***0.841***			
OD	0.478	0.243	***0.800***		
SS1	0.246	0.259	0.372	**1.000**	
TD	0.591	0.282	0.556	0.141	***0.751***

Table 5: Discriminant Validity - Fornell and Larcker Criterion

Note: AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'

Cross Loadings Criterion

Table 6 reveals that the factor loading of all the items is more strongly associated with the underlying construct to which they belong than with the other study construct (Knekta, Runyon & Eddy, 2019). Based on the evaluation of cross-loadings, discriminant validity is therefore achieved.

	AMAT	ED	OD	SS1	TD
AMAT1	0.670	0.165	0.346	0.253	0.321
AMAT2	0.833	0.230	0.387	0.180	0.566
AMAT5	0.588	0.226	0.269	0.078	0.315
ED1	0.288	0.912	0.264	0.286	0.267
ED2	0.184	0.765	0.119	0.120	0.201
OD1	0.477	0.188	0.869	0.217	0.518
OD2	0.393	0.166	0.843	0.398	0.435
OD3	0.184	0.305	0.674	0.343	0.354
SS1	0.246	0.259	0.372	1.000	0.141
TD1	0.507	0.221	0.400	0.160	0.795
TD2	0.469	0.226	0.398	0.041	0.829
TD3	0.332	0.189	0.493	0.119	0.612

Table 6: Cross Loadings

Note: AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'

As shown in Table 7 below, the inter-correlation values for all paired latent variables are less than 1.0, thereby validating the existence of discriminant validity.

	AMAT	ED	OD	SS1	TD
AMAT	1.000				
ED	0.516	1.000			
OD	0.711	0.391	1.000		
SS1	0.345	0.309	0.460	1.000	
TD	1.033	0.456	0.826	0.182	1.000

Table 7: Hetero Trait – Mono Trait Ratio (HTMT) Matrix

Note: AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'

Table 7 testifies that discriminant validity is high since the values are less than 0.8, which is highly recommended by O'Rourke & Hatcher (2013) and Olanipekun, Ahmed, Opoku, and Sutrisna (2022).

Summary of Measurement Model Accuracy Statistics

Table 8 below summarises the descriptive statistics and the measurement model assessment statistics. The mean values below indicate that most respondents slightly disagreed with the measures asked (>1-<4). The standard deviations were less than 2, therefore suggesting that the mean values are a correct reflection of the majority average perceptions.

Research construct		Scale item		Cronbach's Alpha	CR	AVE	Factor Loadings
		Mean	SD				
	AMAT1	3.336	0.988				0.670
AMAT	AMAT2	4.110	0.915				0.833
	AMAT5	3.247	1.101	0.692	0.743	0.596	0.588
ED	ED1	3.377	0.980				0.912
	ED2	3.486	1.055	0.604	0.828	0.708	0.765
	OD1	3.863	0.881				0.869
OD	OD2	3.911	1.079				0.843
	OD3	3.534	1.041	0.737	0.840	0.640	0.674
SS	SS1	3.986	0.921				1.000
	TD1	3.486	0.974				0.795
TD	TD2	3.404	1.044				0.829
	TD3	3.616	1.074	0.612	0.793	0.565	0.612

Table 8: Scale accuracy analysis

Note: AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'; SD= Standard Deviation; CR= Composite Reliability; AVE= Average Variance Extracted;
** Scores: 1 – Strongly Disagree; 3 – Moderately Agree; 5 – Strongly Agree*

Model Fit Summary

Since the model fit statistics are regarded to be still in the development stage – the current study also used the Global Fit Statistic Approach proposed by Tenenhaus, Vinzi, Chatelin & Lauro (2005), to augment the model fit statistics generated by Smart PLS (Chinomona, 2016). The indices examined are SRMR, the CMIN or the Chi-square $\chi 2$ /df), and the Normed Fit Index (NFI). The Standardized Root Square Residual (SRMR) is 0.087, less than the 0.10 threshold Hu and Bentler (1999) recommended. Hence, this confirms a good model fit. Furthermore, the Normed Fit Index (NFI) is 0.800, which is less than the threshold of 0.900, as suggested by Bentler and Bonett (1980). Overall, these results indicate that, by and large, the model fit indices can be deemed to meet the acceptable thresholds recommended in the extant literature marginally.

Model Fit Indices	Acceptable Threshold	Current Study Threshold	Decision: Acceptable/Unacceptable
SRMR	0.1	0.0132	Accept
NFI	0.9	0.862	Accept

Table 9: Model Fit

Overall, R² for AMAT and SS indicates that the research model explains more than 11.0%, 8.7%, 14.5% and 21.2% of the variance in the endogenous variables, respectively. Following the formulae provided by Tenenhaus, Vinzi, Chatelin & Lauro (2005), the global goodness-of-fit (GoF) statistic for the research model was calculated using the equation:

$$\text{GoF} = \sqrt{\overline{\text{AVE}} \ * \ \overline{\text{R}^2}}$$

The calculated global goodness of fit (GoF) is 0.523, which exceeds the threshold of GoF>0.36 suggested by Khojasteh and Lo, 2015. Thus, this study concludes that the research model fits well. The GoF and NFI provided in Table 9 indicate a marginal fit of the data to the proposed conceptual model. Based on this marginal fit – the researcher proceeded to test the proposed hypotheses.

6.4. Structural Model

Figure 3 shows a structural model representing the result for the hypothesis – H1 to H4.

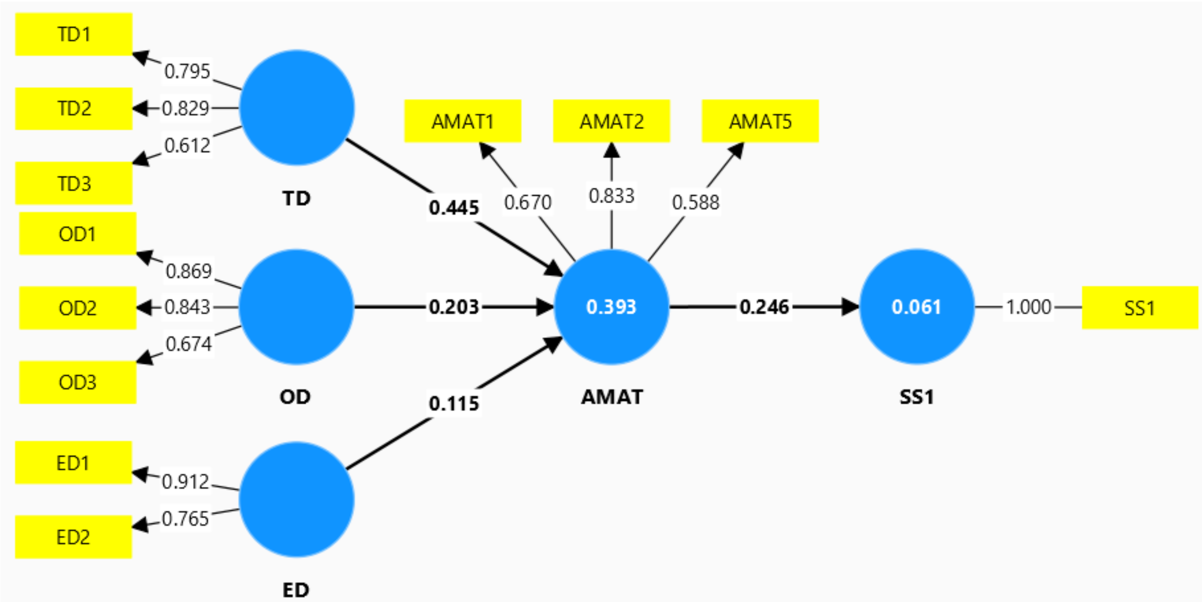

Figure 3: Structural Model

Note: AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'

Four hypotheses were tested, and the path coefficients are provided in Table 9. The significance levels were assessed using p-values and t-statistics. Hypotheses are viewed as significant at a 95% or higher level of significance (≥ 95%), and the p-value is ≤ 0.05 (Hair et al., 2010; Di Leo & Sardanelli, 2020). The t-statistics are expected to be greater than 1.96 for the proposed relationship to be deemed acceptable. Table 9 first provides the proposed hypotheses and path coefficients, followed by t-statistics and p-values, which indicate the significance level of the proposed relationship. Finally, the last column provides the decision taken by the researcher on whether to accept or reject the proposed hypotheses, given the findings. The path coefficients demonstrate the strength of the relationships between the dependent and independent variables (Hsu, 2008). Upon assessing the probability value, which is also referred to as the p-value, it was demonstrated that all four hypotheses postulated were significant at p<0.05.

Hypothesized Relationship	Hypotheses	Path Co-efficient	T Statistics	P Values	Supported/Rejected
TD -> AMAT	**H1**	0.445	5.285	0.000	Supported and significant
OD -> AMAT	**H2**	0.203	2.579	0.010	Supported and significant
ED -> AMAT	**H3**	0.115	1.690	0.091	Supported but insignificant
AMAT -> SS	**H4**	0.246	2.350	0.019	Supported and significant

Table 9: Path Analysis Results

Note: AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'

H1 evaluates whether Technological drivers positively impact the Awareness of Marketing Automation Tools. Based on the results, the relationship between Technological drivers and Awareness of Marketing Automation Tools is inevitably positive. Therefore, the more Technological drivers there are, the more positive the Awareness of marketing automation tools will be. Further to the path modelling results (β=0.445, t=5.285, p=0.000), it is evident that this relationship is robust due to the estimated path modelling equal to 0.445. In other words, Technological drivers positively affect Awareness of Marketing Automation Tools.

Based on the research findings, the relationship between Organisational drivers and Awareness of Marketing Automation Tools is inevitably optimistic. Therefore, the more the Organisational drivers there are, the more positive the Awareness of marketing automation tools will be. Further to the path modelling results (β=0.203, t=2.579, p=0.010), it is evident that this relationship is very strong. In other words, Organisational drivers have a strong positive effect on Awareness of Marketing Automation Tools.

H3 evaluates whether Environmental drivers positively impact the Awareness of Marketing Automation Tools. Based on the results, the relationship between Environmental drivers and Awareness of Marketing Automation Tools is inevitably positive. Therefore, the more Environmental drivers there are, the more positive the Awareness of marketing automation tools will be. Further to the path modelling results (β=0.115, t=1.690-, p=0.091), it is evident that this relationship is weak due to the estimated path modelling equal to 0.115. In other words, Environmental drivers have a weak effect on Awareness of Marketing Automation Tools positively. Hence, H3 is true.

H4 evaluates whether Awareness of Marketing Automation Tools significantly impacts the Sustainability (SS) of ITS'. The results supported the notion that there is a positive relationship between Awareness of Marketing Automation Tools and Sustainability of ITSs. The results revealed that Awareness of Marketing Automation Tools has a positive and significant effect on the Sustainability of ITS' (β=0.246, t=2.350, p=0.019). Based on this study, it can be confirmed that the positive Awareness of Marketing Automation Tools can lead to higher Sustainability of the Impact Tech Startups in South Africa. Hence, H4 was supported.

Mediation Assessment Results

The four-step method offered by Zhao et al., 2010 was used for this research. This method proposes the following procedures: (1) regressing the independent variable on the dependent variable, (2) regressing the independent variable on the mediator, (3) regressing the mediator variable on the dependent variable, and (4) establishing that the mediator value partially or completely mediates the X–Y relationship; the effect of X (independent variable) on Y (dependent variable) controlling for the mediator value should be reduced or zeroed out. To begin the mediation analysis, the significance of the indirect effects was tested.

The indirect effect from TD via AMAT to SS is the product of the path coefficients from TD to AMAT and from AMAT to SS (mediation path 1). The indirect effect from OD via AMAT to SS is the product of the path coefficients from OD to AMAT and from AMAT to SS (mediation path 2). The indirect effect from ED via AMAT to SS is the product of the path coefficients from ED to AMAT and from AMAT to SS (mediation path 3).

To test the significance of these path coefficients' products, the bootstrap routine was run. All other situations under the condition that both the direct effect c' and the indirect effect a×b is significant represent partial mediation. Two types of partial mediation can be distinguished, namely, complementary partial mediation and competitive partial mediation. In a complementary partial mediation, the direct effect c and indirect effect a×b point in the same (positive or negative) direction (Baron and Kenny, 1986). It is an often observed result that a×b and c' are significant and a×b×c' is positive, which indicates that a portion of the effect of X on Y is mediated through M. At the same time, X still explains a portion of Y independent of M. This complementary mediation hypothesis suggests that the intermediate variable explains, possibly confounds, or falsifies the relationships between the independent and dependent variables.

In a competitive partial mediation, the direct effect c' and indirect effect a×b point in a different direction. A negative a×b×c' value indicates the presence of competitive mediation in Step 2. As mentioned above, this shows that a portion of the effect of X on Y is mediated through M, while X still explains a portion of Y that is independent of M. In the past, researchers often focused only on complementary mediation (Zhao et al., 2010). The competitive partial mediation hypothesis assumes that the intermediate variable will reduce the magnitude of the relationship between the independent and dependent variables. However, it is possible that the intermediate variable could increase the magnitude of the relationship between the independent and dependent variables.

	Hypotheses	**Direct Effect**	**95% Confidence Interval (With Bias Correction) of the Direct Effect**	**Significance ($p < 0.05$)?**	**Indirect Effect (via AMAT)**	**95% Confidence Interval (With Bias Correction) of the Indirect Effect**	**Significance ($p < 0.05$)?**	**Decision**
TD -> SS	**H5**	0.110	[0.018, 0.219]	Yes	0.110	0.110	Yes	No Mediation
OD -> SS	**H6**	0.050	[0.003, 0.128]	No	0.050	0.050	No	No Mediation
ED -> SS	**H7**	0.028	[-0.004, 0.079]	No	0.028	[-0.001, 0.084]	No	Partial Mediation

Table 10: Mediation Results

AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'

H5 predicted that Awareness of marketing automation tools would mediate the relationship between Technological drivers and the Sustainability of ITS. The relationship between Technological drivers and SS is very weak (0.110) and statistically significant. Following the mediation analysis procedure in Table 10, we conclude that AMAT partially mediates the Technological drivers of the SS relationship. To further substantiate the type of partial mediation, we compute the product of the direct and indirect effects. Since the direct and indirect effects are both positive, the sign of their product is also positive (i.e., 0.110 x 0.110 = 0.036). Consequently, AMAT represents complementary mediation of the relationship from TD to SS.

H6 predicted that Awareness of marketing automation tools would mediate the relationship between Organisational drivers and the Sustainability of ITS. The relationship from Organisational drivers to Sustainability of ITS is very weak (0.028) and statistically not significant. The bootstrapped unstandardized indirect effect was 0.028 and statistically not significant. Following the mediation analysis procedure in Table 10, we conclude that AMAT does not mediate the OD to SS relationship.

H7 predicted that Awareness of marketing automation tools would mediate the relationship between Environmental drivers and the Sustainability of ITS. The relationship from Environmental drivers to the Sustainability of ITS is very weak (0.050) and statistically not significant. The bootstrapped unstandardized indirect effect was 0.050 and statistically not significant. Following the mediation analysis procedure in Table 10, we conclude that AMAT does not mediate the ED to SS relationship.

Model Prediction Assessment

By and large, model prediction assessment focuses on the model's explanatory power and model predictive power. This study assesses the model's explanatory power using R^2 and F^2, while the model's predictive power is assessed using Q^2. Model explanatory power is assessed using the R-squared (R^2) and F-squared (F^2) statistics. R-squared statistic explains the variance in the endogenous variable explained by the exogenous variable(s). In other words, it simply means how much change in the dependent variable can be explained by one or more independent variable(s). In the current study context, AMAT is influenced by TD, OD, and ED, which has an R-squared value of 0.393. This implies that TD, OD and ED explain 39.3% of AMAT). Furthermore, SS is influenced by AMAT, which has an R^2 of 0.061, hence implying that AMAT accounts for 6.1% of SS.

According to Hair et al. (2013), R^2 values of 0.75, 0.50, or 0.25 for endogenous latent variables can, as a rough rule of thumb, be respectively described as substantial, moderate or weak. Since the R^2 for AMAT is 0.393 and for MP is 0.061, the R^2 can be deemed weak for AMAT and SS, respectively.

F-squared (F^2) is the change in R^2 when an exogenous variable is removed from the model. In other words, F^2 is the effect size. According to Cohen (1988) and Hair et al. (2013), an effect size of $F^2 >= 0.02$ is deemed minor, $F^2 >= 0.15$ is regarded as medium, and $F^2 >= 0.35$ is deemed significant. In the context of this study, the results show that TD, OD, and ED have an effect size of 0.219, 0.020, and 0.046, respectively – hence, they can be deemed to have a medium effect size. Thus, removing TD is expected to have a medium effect size on AMAT, while removing (OD and ED) is expected to have a negligible effect size on AMAT. However, the AMAT range is 0.065. Hence, it can be deemed to have a negligible effect size. This means that removing this variable will have a negligible effect on the dependent variable, namely, SS.

Model Predictive Relevance

In this study, Q-squared (Q^2) was used to measure whether a model has predictive relevance or not. A model is deemed to have predictive relevance when Q^2 is greater than 0. Thus, $Q^2>0$ is regarded as good. Furthermore, Q^2 establishes the predictive relevance of endogenous constructs. Q^2 values above zero indicate that your values are well reconstructed and that the model has predictive relevance. Based on the results provided in Table 11, this study shows that the Q^2 for the latent and endogenous variables AMAT and SS are 0.343 and 0.047, respectively. For AMAT, the value is substantially above zero; therefore, it can be concluded that the current study model has strong predictive power and relevance.

Predictor Variables	Outcome Variables	R-Squares (R^2)	F-Squared (F^2)	Q-Squared (Q^2)
TD	AMAT	0.393	0.219	0.343
OD			0.020	
ED			0.046	
TD	SS	0.061	0.219	0.047
OD			0.020	
ED			0.046	
AMAT			0.065	

Table 11: Summary of Predictive Relevance Assessment

Validating Higher Order Construct

'Marketing Automation Tools Adoption Drivers' was the higher-order construct in the study based on three lower-order dimensions (Technological drivers, organisational drivers and environmental drivers). To establish the highest order construct validity, Outer Weights, Outer Loadings and VIF. The outer weights were significant (Hair et al., 2016). Furthermore, outer loadings were more important than 0.50 for each lower-order construct (Sarstedt et al., 2019). Finally, VIF values were assessed to check collinearity, and all VIFs were less than the recommended value of 5 (Hair et al., 2016). Since all criteria were met, the HOC validity was established.

HOC	LOCs	Outer Weights	T Statistics	P Values	Outer Loadings	VIF
MATAD	**ED**	0.288	4.754	0.000	0.615	1.179
	OD	0.450	9.886	0.000	0.811	1.406
	TD	0.526	9.006	0.000	0.871	1.498

Table 12: Higher Order Construct Validity

Note: MATAD= Awareness of Marketing Automation Tools adoption drivers; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers

Structural Model Assessment

The next step in structural equation modelling is assessing the hypothesized relationship to substantiate the proposed hypotheses. The structural model of the study was evaluated by examining p-values and standardized regression coefficients.

Assuming the hypothesized measurement and structural model had been evaluated and finalized, the next step was to examine causal relationships among latent variables using path analysis (Nusair et al. 2010). Table 13 displays the estimation results derived from hypothesis testing for this study. The table shows the proposed hypotheses, the path coefficients, the t-statistics, and whether a hypothesis is rejected or supported. Literature states that t > 1.96 coefficients indicate strong relationships between latent.

Structural Model

Figure 3 shows a structural model representing the result for the hypothesis – H1 to H2.

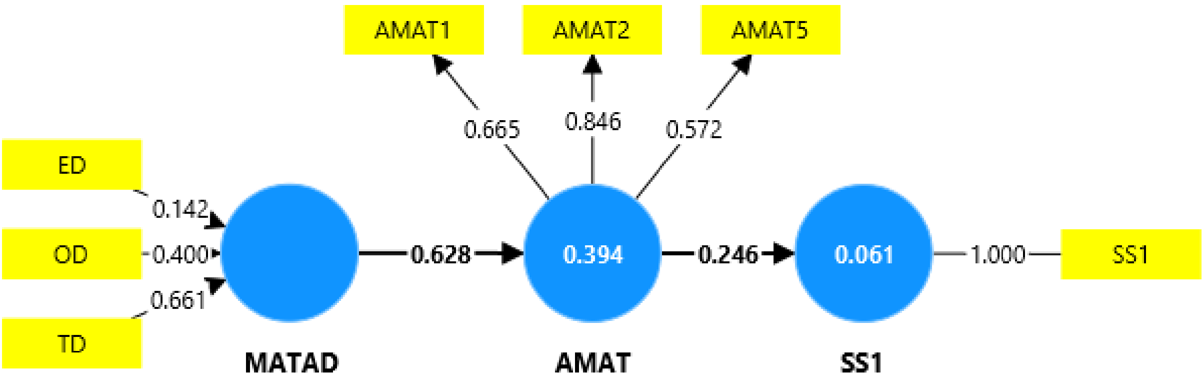

Figure 3: Structural Model

Note: AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'

Two hypotheses were tested, and the path coefficients are provided in Table 6.20. The significance levels were assessed using p-values and t-statistics. Hypotheses are viewed as significant at a 95% or higher level of significance (≥ 95%), and the p-value is ≤ 0.05 (Hair et al., 2010; Di Leo & Sardanelli, 2020). The t-statistics are expected to be greater than 1.96 for the proposed relationship to be deemed acceptable. Table 13 first provides the proposed hypotheses and path coefficients, followed by t-statistics and p-values, which indicate the significance level of the proposed relationship. Finally, the last column provides the decision taken by the researcher on whether to accept or reject the proposed hypotheses, given the findings. The path coefficients demonstrate the strength of the relationships between the dependent and independent variables (Hsu, 2008). Upon assessing the probability value, which is also referred to as the p-value, it was demonstrated that all the hypotheses postulated were significant at p<0.05.

Hypothesized Relationship	Hypotheses	Path Co-efficient	T Statistics	P Values	Supported/Rejected
MATAD -> AMAT	**H1**	0.246	2.335	0.020	Supported and significant
AMAT -> SS	**H2**	0.620	8.914	0.000	Supported and significant

Table 13: Path Analysis Results

Note: AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'

H1 evaluates whether Marketing Automation Tools Adoption Drivers (MATAD) positively impact the Awareness of Marketing Automation Tools. Based on the results obtained, the relationship between MATAD and Awareness of Marketing Automation Tools is inevitably positive. Therefore, the more MATADs there are, the more positive the awareness of marketing automation tools will be. Further to the path modelling results (β=0.620, t=8.914, p=0.000), it is evident that this relationship is robust due to the estimated path modelling equal to 0.620. In other words, MATAD has a strong positive effect on the Awareness of Marketing Automation Tools. Hence, H1 is sustained.

H2 evaluates whether Awareness of Marketing Automation Tools has a significant impact on the Sustainability (SS) of ITS. The study's results support the existence of a positive relationship between the Awareness of Marketing Automation Tools and the Sustainability of ITS. The results revealed that Awareness of Marketing Automation Tools has a positive and significant effect on the Sustainability of ITS (β=0.246, t=2.335, p=0.020). Based on this study, it can be confirmed that the positive Awareness of Marketing Automation Tools can lead to higher Sustainability of the Impact Tech Startups in South Africa. Hence, H2 was supported.

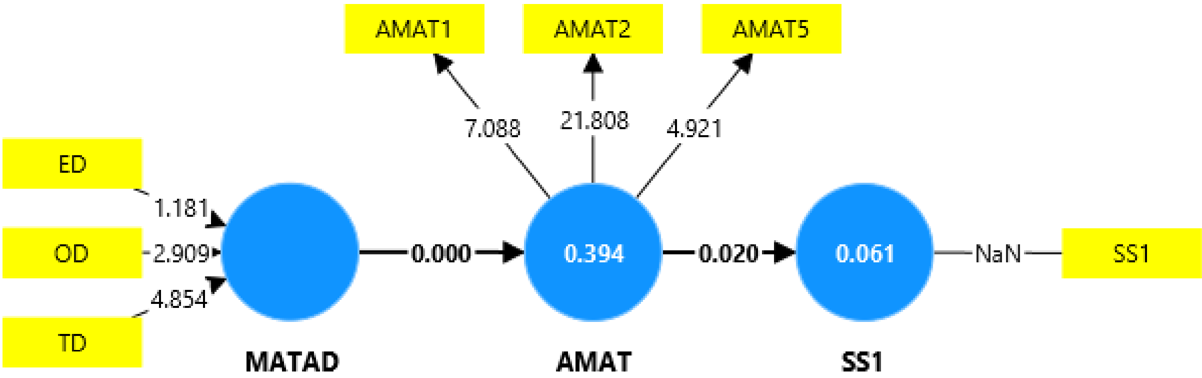

Figure 4: Bootstrapping Results

Note: AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'

Mediation Assessment Results

The four-step method offered by Zhao et al. (2010) was used for this research. This method proposes the following procedures: (1) regressing the independent variable on the dependent variable, (2) regressing the independent variable on the mediator, (3) regressing the mediator variable on the dependent variable, and (4) establishing that the mediator value partially or completely mediates the X–Y relationship; the effect of X (independent variable) on Y (dependent variable) controlling for the mediator value should be reduced or zeroed out. To begin the mediation analysis, the significance of the indirect effects was tested.

The indirect effect from MATAD via AMAT to SS is the product of the path coefficients from MATAD to AMAT and from AMAT to SS (mediation path 1). To test the significance of these path coefficients' products, the bootstrap routine was run. All other situations under the condition that both the direct effect c' and the indirect effect a×b is significant represent partial mediation. Two types of partial mediation can be distinguished: complementary partial and competitive partial mediation.

Complementary Partial Mediation

In a complementary partial mediation, the direct effect (c) and indirect effect a×b point in the same (positive or negative) direction (Baron and Kenny, 1986). It is an often observed result that a×b and c' are significant and a×b×c' is positive, which indicates that a portion of the effect of X on Y is mediated through M. At the same time, X still explains a portion of Y independent of M. This complementary mediation hypothesis suggests that the intermediate variable explains, possibly confounds, or falsifies the relationships between the independent and dependent variables.

Competitive Partial Mediation

In a competitive partial mediation, the direct effect c' and indirect effect a×b point in a different direction. A negative a×b×c' value indicates the presence of competitive mediation in Step 2. As mentioned above, this indicates that a portion of the effect of X on Y is mediated through M, while X still explains a portion of Y that is independent of M. In the past, researchers often focused only on complementary mediation (Zhao et al., 2010). The competitive partial mediation hypothesis assumes that the intermediate variable will reduce the magnitude of the relationship between the independent and dependent variables. However, it is possible that the intermediate variable could increase the magnitude of the relationship between the independent and dependent variables.

	Direct Effect	**95% Confidence Interval (With Bias Correction) of the Direct Effect**	**Significance ($p < 0.05$)?**	**Indirect Effect (via AMAT)**	**95% Confidence Interval (With Bias Correction) of the Indirect Effect**	**Significance ($p < 0.05$)?**	**Decision**
MATAD -> SS	0.155	[0.017, 0.305]	Yes	0.155	[0.023, 0.311]	Yes	Partial Mediation

Table 14: Mediation Results

AMAT= Awareness of Marketing Automation Tools; ED= Environmental drivers; OD= Organisational drivers; TD= Technological drivers; SS= Sustainability of ITS'

H3 predicted that Awareness of marketing automation tools would mediate the relationship between MATAD and the Sustainability of ITS. The relationship between MATAD and SS is very weak (0.155) and statistically significant. Following the mediation analysis procedure in Table 15, we conclude that AMAT partially mediates the MATAD to SS relationship. To further substantiate the type of partial mediation, we compute the product of the direct and indirect effects. Since the direct and indirect effects are both positive, the sign of their product is also positive (i.e., 0.155 x 0.155 = 0.024). Consequently, AMAT represents complementary mediation of the relationship from MATAD to SS.

Overall analysis of hypotheses testing results

The path coefficients for H1 and H2 were 0.246 and 0.620, respectively. According to these findings, all the relationships that have been hypothesized have a positive link. The research shows that Marketing Automation Tools Drivers (MATD) moderately affect Awareness of Marketing Automation Tools (β=0.246). In contrast, Awareness of Marketing Automation Tools has the most substantial positive relationship with the Sustainability of ITS (β=0.620).

Model Prediction Assessment

By and large, model prediction assessment focuses on the model's explanatory power and model predictive power. This study assesses the model's explanatory power using R^2 and F^2, while the model's predictive power is estimated using Q^2.

Model Explanatory Relevance

Model explanatory power is assessed using the R-squared (R^2) and F-squared (F^2) statistics. R-squared statistic explains the variance in the endogenous variable explained by the exogenous variable(s). In other words, it simply means how much change in the dependent variable can be explained by one or more independent variable(s). In the current study context, AMAT is influenced by MATAD, which has an R-squared value of 0.394. This implies that MATAD explains 39.4% of AMAT. Furthermore, SS is influenced by AMAT, which has an R^2 of 0.061, hence implying that AMAT accounts for 6.1% of SS.

According to Hair et al. (2013), R^2 values of 0.75, 0.50, or 0.25 for endogenous latent variables can, as a rough rule of thumb, be respectively described as substantial, moderate or weak. Since the R^2 for AMAT is 0.393 and for MP is 0.061, the R^2 can be deemed weak for AMAT and SS, respectively.

F-Squared (F^2) is the change in R^2 when an exogenous variable is removed from the model. In other words, F^2 is the effect size. According to Cohen (1988) and Hair et al. (2013), an effect size of F^2>= 0.02 is deemed minor, F^2>= 0.15 is regarded as medium, and F^2>= 0.35 is deemed large. In the context of this study, the results show that

MATAD has an effect size of 0.219 respectively – hence, it can be deemed to have a medium effect size. Thus, removing MATAD is expected to have a medium effect size on AMAT. However, the AMAT range is 0.065, the smallest effect size in the model. Removing this variable will have a negligible effect on the dependent variable, namely, SS.

Model Predictive Relevance

In this study, Q-squared (Q^2) was used to measure whether a model has predictive relevance or not. A model is deemed to have predictive relevance when Q^2 is greater than 0. Thus, $Q^2>0$ is regarded as good. Furthermore, Q^2 establishes the predictive relevance of endogenous constructs. Q^2 values above zero indicate that your values are well reconstructed and the model has predictive relevance. Based on the results provided in Table 15, this study shows that the Q^2 for the latent and endogenous variables AMAT and SS are 0.358 and 0.048, respectively. For AMAT, the value is substantially above zero; therefore, it can be concluded that the current study model has strong predictive power and relevance.

Predictor Variables	Outcome Variables	R-Squares (R^2)	F-Squared (F^2)	Q-Squared (Q^2)
MATAD	AMAT	0.394	0.219	0.358
AMAT	SS	0.061	0.065	0.048

Table 15: Summary of Predictive Relevance Assessment

Discussion of the Findings

Regarding the Awareness of Marketing Automation Tools and adoption barriers, 43.9% of participants agreed that ITSs do not adopt marketing automation tools because of a lack of Awareness. Chakraborti et al. (2022), as cited in El-Shihy and Mohamed (2023, p.91), argue that a lack of awareness about the benefits of marketing automation can serve as a barrier to adopting marketing automation tools. Soni (2023, p.3) stated that efficiency and scalability are drivers of marketing automation adoption.

Most respondents, 57.5%, agreed that the perceived relative advantages of marketing automation tools impact the adoption of these tools by ITSs since marketing automation enhances productivity by automating repetitive tasks and makes for more accurate decision-making (Mannel, 2019). Soni (2023, p.5) adds that another driver for adopting generative Generative AI into digital marketing is that it improves customer engagement using chatbots.

Kalimuthu et al. (2024, p.421) argued that marketing automation is complex and that its implementation requires significant technical expertise and resources, and Startups are more likely to adopt technology if it is seen to be convenient and easy to use (Ebrahim and van den Berg, 2024, p.9).

Concerning the the organisational drivers of the adoption of marketing automation tools, a significant 69.2% of the respondents agreed that top management support impacts the adoption of marketing automation. Alsaad et al. (2017), as cited in Tobon (2017, p.27), stated that top management support is a driver of marketing automation adoption since "It guarantees the sufficient allocation of resources to adopt new technologies." Mehta and Pradhan (2024, p.29135) also argued that "top management involvement plays an important determinant of social media adoption as supported in other research."

When asked about the impact of the availability of financial support, the vast majority (74.7%) of respondents agreed that it influenced adoption decisions. According to Nurlan, Ahmad, Singh and Shifighi (2024, p.324), budget constraints hinder startups' adoption of marketing automation. Kedi et al. (2024, p.1983) assert, "One of the primary marketing challenges specific to SMEs is the limited financial resources available for marketing initiatives. This often results in smaller marketing budgets, which can restrict the ability to invest in cutting-edge technologies."

According to Musa et al. (2013), as cited in Smidt and Sokonya (2022), one of the reasons behind the low adoption of marketing automation is a lack of digital skills. Nurlan et al. (2024, p.324) opined that lacking human resources and skills is a barrier to adopting marketing automation. Soni (2023, p.6) argues that talent and expertise requirements are barriers to adopting Generative AI in digital marketing. "The effective implementation and management of AI tools requires a blend of skills, including expertise in AI and machine learning, data science and digital marketing strategies."

Ahmad et al. (2018), as cited in Fu et al. (2024, p.6), stated that "a high level of skill, knowledge and competence among employees, as perceived in employed capability, facilitates SMEs in the process of adopting new technology."Ebrahim and van den Berg (2024, p.8) stated that "digital incompetency is a barrier to technology adoption among the older respondents in this research sample. With the younger respondents, the data indicate that the younger respondents find technology easier to use. As a result, they have a positive attitude towards technology adoption."

A significant proportion (76.7%) of the respondents concurred that the adoption of marketing automation tools by ITS positively impacted its sustainability. Otika et al. (2022) opined that e-marketing is essential to the success of startups. Reddy (2021), as cited in Rameshkumar (2022, p.18) stated that "digital marketing platforms are useful to the farmers as they increase the selling price and reduce the marketing cost of their agriculture output." According to Bvuma and Manerwick (2020, p.9), "Overall, the twenty-one (21) participants in their study perceived ICT adoption as a necessity towards growth and sustainability for their business. They believed that ICT would assist them to stay competitive and grow their business." El-Shihy and Mohamed (2023, p.109) confirmed that "startups' Digital Marketing Adoption had a significant impact on performance, which was in line with other studies such as Qalati et al. (2021) and Ahmad et al. (2019)."

Nyagdza et al. (2022) opined that the number of Africans using social media platforms has grown exponentially in the post-2000 period and therefore, SMEs need to take advantage of this to stay competitive (Taiminen & Karjaluoto, 2015, as cited in Virtanen et al., 2017). Jones et al. (2015), as cited in Virtanen et al. (2017), posited that social media marketing is affordable and, therefore, well-suited to SMEs because they lack larger companies' resources.

According to Patil et al. (2022) and Chakraborti et al. (2022), digital marketing is critical to the success of tech startups because it helps them achieve meaningful customer engagement at a low cost. Digital marketing is more affordable and delivers better Return on Investment (ROI) than traditional advertising (Pandey and Tilak, 2022). El-Shiny and Mohamed (2023, p.91) concurred that "digital marketing adoption is vital for the success of startups." Anane-Simon and Atiku (2024, p.137) opined that "in Industry 4.0, AI technology has the potential to reshape the landscape of innovation and success for these startups."

This study confirmed that Awareness of marketing automation tools can lead to higher Sustainability of the Impact Tech Startups in South Africa.

The results showed that Awareness of Marketing Automation Tools (AMAT) would mediate the relationship between MATAD and the Sustainability (SS) of ITS. Following the mediation analysis procedure, it can be concluded that AMAT partially mediates the MATAD-to-SS relationship. The product of the direct and indirect effects were computed to further substantiate the partial mediation type. Since the direct and indirect effects were both positive, the sign of their product was also positive (i.e., 0.155 x 0.155 = 0.024). Consequently, AMAT represented complementary mediation of the relationship from MATAD to SS.

According to these findings, all the relationships that have been hypothesised have a positive link. Research shows that Marketing Automation Tools Drivers have a moderate effect on Awareness of Marketing Automation Tools (β=0.246). In contrast, Awareness of Marketing Automation Tools has the most substantial positive relationship with the Sustainability of ITS (β=0.620). Based on the research findings, the framework depicted in Figure 5 is proposed to sustain ITSs in South Africa.

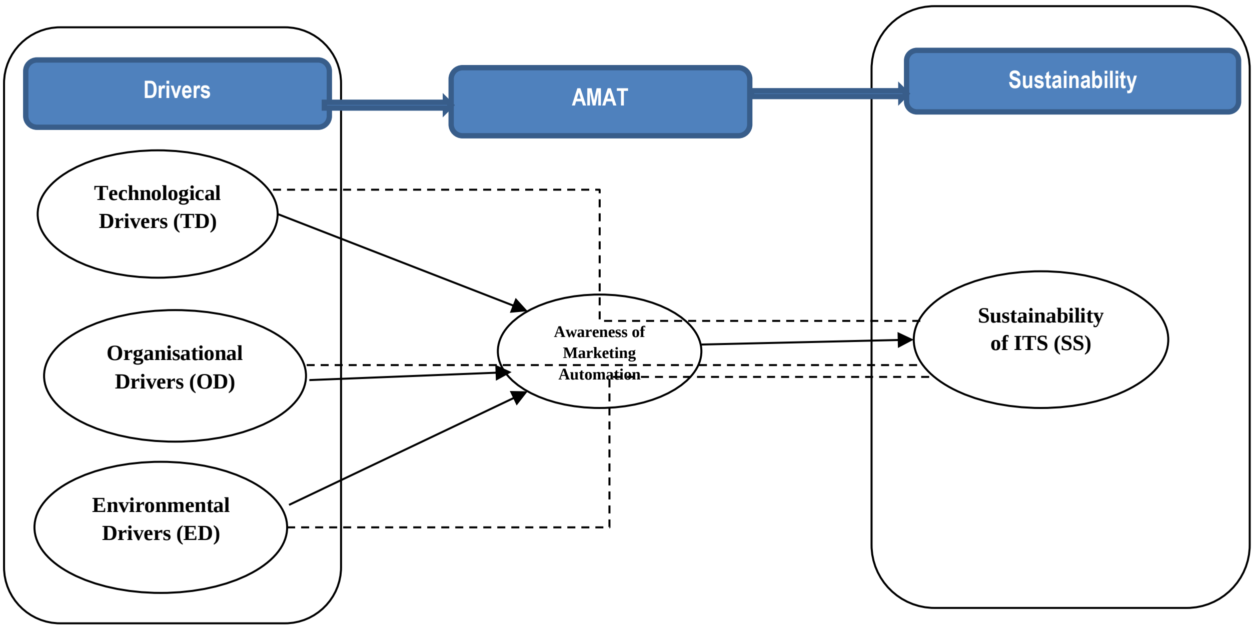

Figure 5: Proposed Framework

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