“Predicting smart wrist wearable adoption intention among South African youth”

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PREDICTING SMART WRIST WEARABLE ADOPTION INTENTION AMONG SOUTH AFRICAN YOUTH

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Abstract

Smart wrist wearables (SWWs) represent the leading segment in the multi-billion-dollar global fitness tracker industry. Despite the robust and thriving global market, South Africa remains far behind in adoption, penetration rate and market value. As such, this study aims to predict SWW adoption intention among South African youth by examining the influence of perceived usefulness, perceived ease of use, information availability, social image, brand name, perceived performance risk, perceived cost, and attitude. The study surveyed 312 South African Parkrun attendees aged 18-34 using a self-administered questionnaire. The youth market was specifically targeted as they represent the primary users of wearable technology and because of their high digital engagement. SPSS and AMOS v. 27 were used for model validation and hypothesis testing through confirmatory factor analysis and path analysis, respectively. The results show that device ease of use boosts perceived usefulness ($\beta = 0.82$, $p < 0.01$), consequently influencing attitudes ($\beta = 0.78$, $p < 0.01$) and adoption intentions. Information availability ($\beta = 0.20$, $p < 0.01$) significantly influences adoption intentions, where perceived performance risk ($\beta = 0.22$, $p < 0.01$) echoes this finding for attitude. Social image ($\beta = -0.11$, $p < 0.05$) and perceived cost ($\beta = -0.47$, $p < 0.01$) had a significant, adverse effect on respondents' attitude towards SWWs. Notably, brand name ($\beta = -0.01$, $p > 0.01$) plays no notable role in attitude formation and ultimate adoption intentions. These findings offer actionable insights for SWW brands seeking to develop targeted, competitive strategies.

Keywords Technology Acceptance Model, wearable technology, user acceptance, emerging markets, digital health devices

JEL Classification M31, D12, O33

INTRODUCTION

South Africa's dynamic technological landscape and growing focus on digital health innovations (National Department of Health, 2020) make it a compelling setting to study smart wrist wearable (SWW) adoption. Despite notable economic inequalities, the country's youth are digitally engaged, socially influenced, and brand-aware (Azionya & Overton-de Klerk, 2021), making them a lucrative market segment in this regard. This segment frequently uses mobile and wearable technology for communication, entertainment, and health tracking (Muller, 2022). Nonetheless, challenges like cost, trust in brands, and doubts about feature relevance may restrict broader uptake in South Africa.

In South Africa, smartwatch adoption lags behind global trends, with the country ranking 39th worldwide with only 19.4% of internet users aged 16 to 64 reporting owning a smartwatch (Kemp, 2023), whereas the key global segment includes consumers aged 18-34 years old. The fitness tracker market remains relatively underdeveloped, with a projected national penetration rate of just 10.07% in 2025, expected to rise to 12.26% by 2029 (Statista, 2025). Market value is similarly limited, forecasted at USD 228.97 million in 2025, with a slow growth trajectory reaching USD 278.65 million by 2029 (Statista, 2025). Despite global brand presence, South Africa's smart wrist wearable sector has yet to achieve comparable success, highlighting an urgent need for strategic intervention.

1. LITERATURE REVIEW

The global fitness tracker market has experienced substantial growth, with its value projected to rise from USD 72.08 billion in 2025 to USD 290.85 billion by 2032 (Rawal, 2025). This surge is largely driven by continuous technological innovation, such as integrating AMOLED displays and advanced health monitoring features. These include heart rate tracking, blood oxygen saturation (SpO_2), stress levels, VO_2 max, menstrual cycle tracking (Research & Markets, 2025), as well as ECG, blood pressure, heart rate variability (HRV), respiratory rate, and body temperature monitoring (Rawal, 2025). These capabilities extend far beyond traditional step counting or calories and distance tracking. Other contributing factors to market expansion include rising consumer health awareness, the increasing application of wearables in healthcare for remote vital sign monitoring, the incorporation of fitness devices in corporate wellness programs, and the growing popularity of sports and fitness lifestyles (Verified Market Research, 2025).

Wrist-based health wearables, namely fitness bands and smartwatches, led the global fitness tracker market in 2024 (Rawal, 2025), with smartwatches projected to generate USD 164.7 billion in revenue by 2032 (Barai & Mutreja, 2023). As of 2024, there were approximately 454.69 million smartwatch users and 398.16 million fitness tracker users. These figures are expected to rise to 740.53 million and 524.93 million users by 2029, respectively (Pangarkar, 2025). These estimates attest to the robustness of the global smart wrist wearable market. Leading global brands include Fitbit, Samsung, Amazfit, TomTom, Huawei, Garmin, Fossil, Apple, Sony (Barai & Mutreja, 2023), as well as Pebble, Xiaomi, Polar, Nike (Rawal, 2025), and Withings (Research and Markets, 2025). Despite the robustness of the global smart wrist wearable market, there is limited empirical consumer behavior research within the South African context, particularly among the youth market.

South Africa is a compelling setting for this study because of its socio-economic and consumer behavior landscape. The country's persistent digital divide creates significant disparities in information availability across urban-rural and socioeconomic boundaries (Govender, 2024), including awareness of new technologies. Moreover, South Africa's multilingual population and varying digital literacy levels create substantial perceived ease of use barriers. Economic pressures from high unemployment and resource constraints amplify the importance of perceived usefulness and perceived cost of new or unfamiliar technologies in adoption decisions (Mangadi & Petersen, 2024). Besides, because of South Africa's high living costs, Benissan (2024) opines that there is less disposable income to purchase luxury goods. Furthermore, intense competition between global and local brands, coupled with brand-sensitive consumers, typically the youth, makes brand name an important differentiator (Appiah-Nimo et al., 2024).

In studying consumer behavior and innovative product development, particularly buying habits, the youth segment is generally defined as adult consumers from early adulthood (Szwajlik, 2019) through their early thirties (Dinesh & Divyabharath, 2023), despite variations in generational cohort classifications. This study specifically focused on the South African youth market for several reasons. South African youth represent a strategically important market for smart wrist wearables due to several psychological and behavioral traits, such as their high mobile connectivity, growing health consciousness driven by rising non-communicable disease awareness, and status-driven consumption patterns where wearable technology serves as a social symbol of modernity and aspiration despite economic constraints (Muller, 2022). This demographic's adoption of fitness trackers and smartwatches is further accelerated by their digital nativity, active social media engagement, where health tracking and achievement sharing enhance social image, and increasing participation in wellness trends, making them

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early adopters who influence broader market penetration in emerging economies (Gulati et al., 2024). While considering these market factors, it is vital to emphasize that South African youth can feasibly access SWWs due to the low acquisition cost for an average-priced or budget-friendly device, despite Benissan's (2024) notion of it being an exclusive, luxury market. For instance, Aamoth (2025) advocates that new or constrained users use one of the four budget-friendly devices, with the two lowest-priced devices costing ZAR866 (± USD 54) and R1212 (± USD 74). All the listed devices can produce essential activity and health-related metrics. Further substantiating the affordability among this study's consumer segment is Jacob's (2024) report that 18- to 24-year-old individuals in South Africa have an average taxable income of R99 587 (± USD 5,975) and 25- to 34-year-olds R245 822 (± USD 15,340.50). Therefore, there are acceptable probabilities, with proper strategizing and promotional efforts, that the 20.9 million employed South Africans aged 18 to 34 (Stats SA, 2025) will use their disposable income to purchase SWWs.

Thus, considering this consumer segment's psychological and behavioral tendencies, together with economic conditions within their country, gaining insight into the adoption intentions of South African youth is crucial within this brand-saturated and economically diverse context. With nearly 90% of the South African market still untapped, global brands have a timely and strategic opportunity to expand their presence and market share.

Therefore, tapping into this emerging market effectively requires actionable, data-driven insights grounded in consumer perceptions. Understanding these perceptions and how they shape attitudes and behaviors necessitates a structured theoretical framework. While several international studies from countries such as the United States, China, South Korea, and Romania have successfully applied established models to examine wearable technology adoption, South African research remains limited. While one foundational study profiled South African Millennials' wrist-based fitness trackers (Hattingh & Muller, 2022), it reported only descriptive statistics to convey the sample's perceptions regarding several factors. The findings from the latter study are severely limited in terms of practical explanatory power, whereas this new investigation addresses a critical gap in behavioral prediction, which extends far beyond mere perceptions. Thus, the present study introduces a tailored, theoretically informed model designed to predict South African youths' smart wrist-wearable adoption intentions. These insights provide a foundation for targeted brand strategies aimed at unlocking market potential and driving adoption within a distinct and growing segment within the broader wearables category.

Davis's (1989) Technology Acceptance Model (TAM), a widely recognized and influential framework for predicting consumers' willingness to adopt new technologies (Solomon, 2018), guided this investigation into SWWs. The selection of TAM is supported by its successful application in numerous related studies, including research on fitness application usage intention among American consumers (Roh et al., 2023), sports and smart wearables in China (Wang et al., 2023; Gao et al., 2016), wearable activity trackers among South African millennials (Muller, 2022), wearable technology usage by Romanian students (Felea et al., 2021), healthcare wearables among Generation Z (Cheung et al., 2020) and sports wearables (Kim & Chui, 2018) in Hong Kong, fitness wearables among American employees (Lunney et al., 2016), and smartwatches among South Korean users (Choi & Kim, 2016; Kim & Shin, 2015), as well as wearables in general among the same population (Yang et al., 2016).

According to the TAM, the primary dependent variables indicating technology acceptance are attitude (ATT) and behavioral intention. These are influenced by two key factors: perceived usefulness (PU) and perceived ease of use (PEOU) (Kim & Shin, 2015; Davis, 1989). Behavioral intention, or adoption intention (AI) in this study's context, represents an individual's commitment to engage in a specific behavior, which is shaped by their positive disposition toward performing that behavior (Ajzen, 1991). An individual's attitude toward using technology reflects the degree of positive or negative value they associate with the device (Choi & Kim, 2016), and this attitude typically strengthens as the perceived benefits of the technology become clearer (Gao et al., 2016). Therefore, when consumers develop a favorable attitude toward using SWWs, their adoption intentions increase (Lunney et al., 2016). Furthermore, the theory posits that PU, defined as the belief that smart wrist wearables can improve one's health, productivity, or task performance, and PEOU, the assumption that the device is simple and requires minimal effort to use, both play a direct role in shaping consumers' attitudes and their intentions to adopt the technology.

Many of the aforementioned studies applied the TAM and analyzed more complex models with additional variables, such as data analysis, real-time monitoring, simplicity of operation, aesthetic design (Wang et al., 2023), functionality, compatibility, visual attractiveness (Yang et al., 2016), innovativeness, eWOM referrals (Cheung et al., 2020) and perceived enjoyment (Muller, 2022). Regardless, this current study aimed to produce an adoption model containing key factors primarily associated with the target demographic's behavior and personality traits, relying on the TAM as a departure point. Supported by Ajzen's (1991) declaration that attitude is the foremost influencing factor that determine behavioral intentions, this study's foundational nine-factor model approached understanding South African youth consumers' SWW adoption behavior through direct analysis of most variables on their attitudes. An established SWW adoption behavior model opens avenues for future research to uncover the critical, intricate interrelationships between various and a combination of variables, including mediating effects.

Consequently, due to the limitations of relying on overly complex models to understand SWW adoption behavior in an emerging African market and supported by a review of the literature, this study extends the TAM by incorporating five additional variables, namely information availability, social image, brand name, perceived cost and performance risk.

Smart wrist wearable brands offer a wide range of models that vary in complexity, pricing, user interfaces (UIs), and companion apps. Each brand's device is designed to generate and present distinct data points, metrics, and screen displays, many of which users can customize, depending on the model's capabilities. The inclusion of particular features and functions significantly influences consumers' decisions to adopt wearable devices (Adapa et al., 2018), especially since immediate and convenient access to activity-related information is considered a key benefit of the user experience (Shin, 2009). Huang et al. (2017) define information availability (IA) as the perceived ease and promptness of accessing relevant data, particularly for tracking physical activities. However, efforts to enhance IA may carry cost and risk implications, which remain inconclusive in terms of their positive or negative effect on consumer adoption.

In terms of social image, research by Jeong et al. (2017) highlight the influence of social image on young adults' decisions to adopt wearable devices, while Yang et al. (2016) underscore the role of perceived technological value in shaping this behavior. Yang et al. (2016) further define social image (SI) as the extent to which individuals believe that using wearable devices can earn them respect and admiration from others. This social image has a powerful impact on how users are perceived by peers, often encouraging them to keep up with fashion trends to experience a sense of belonging and social approval (Adapa et al., 2018; Rauschnabel & Ro, 2016). A prior study revealed that social image or peer influence is a significant contributor to consumers' attitudes towards wearable activity trackers (Muller et al., 2018).

Brand name (BN), the third additional variable, often reflect personal tastes, identity, and social standing (Morton, 2002). Through this form of personal branding, individuals enhance their self-image and communicate who they are, which encourages them to align with brands that represent their aspirational identity (Yang et al., 2016). A prior study reports the significance of brand name in contributing to consumers' attitudes towards wearable activity trackers (Muller et al., 2018).

With regard to performance risk and cost as the last additional variables, Shin (2007) suggests that consumers typically assess products by comparing the perceived benefits with the overall costs, which encompass not only the price but also the time and effort required to obtain them. Phonthanukitithaworn et al. (2015) define perceived cost (PC) as the degree to which an individual believes that using a given technology will

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incur monetary costs. In this study's context, perceived cost refers to the financial expense associated with buying and using smart wrist wearable technology. Smart wrist wearable brands aim to balance production expenses, profit margins, brand reputation, and market positioning with consumers' willingness to pay. Consequently, product pricing is a strategic decision designed to position devices as affordable and valuable in the eyes of the consumer (Muller, 2022). Conversely, Shin (2009) notes that high prices often serve as a major deterrent, particularly for non-users, even if they find the devices beneficial and enjoyable.

Closely linked to the cost of acquiring a product is the perceived performance risk that consumers, especially those unfamiliar with the technology, associate with smart health wearables (Muller, 2022). In this regard, a consumer would typically expect an expensive smart wrist wearable to work without error; therefore, the higher the device price, the lower the perceived risk associated with the technology. The subjective nature of consumer perception makes this challenging for brands to mitigate. Wu and Wang (2005) explain that consumers may hesitate to purchase high-priced devices due to concerns that the product may not meet their expectations. Supporting this, Hwang (2016) identified perceived performance risk as a critical factor influencing the adoption of technological innovations, such as solar-powered clothing. In the context of this study, perceived performance risk (PPR) refers to the fear that a smart wrist wearable might not perform as intended or deliver accurate, meaningful results (Nasir & Yurder, 2015). As such, if users doubt the device's ability to track health metrics and physical activity reliably, their likelihood of adopting it decreases. Conversely, confidence in performance may enhance consumers' attitude towards smart wrist wearables and their subsequent adoption intentions.

In conclusion, smart wearable technologies have attracted increasing attention in consumer behavior research, with prior studies predominantly focused on developed markets. However, limited empirical evidence exists on the factors influencing wearable adoption within emerging markets such as South Africa, particularly among youth.

Drawing on the TAM and related consumer behavior constructs, this study aims to predict smart wrist wearable adoption intention among South African youth by examining the influence of perceived usefulness, perceived ease of use, information availability, social image, brand name, perceived performance risk, perceived cost, and attitude.

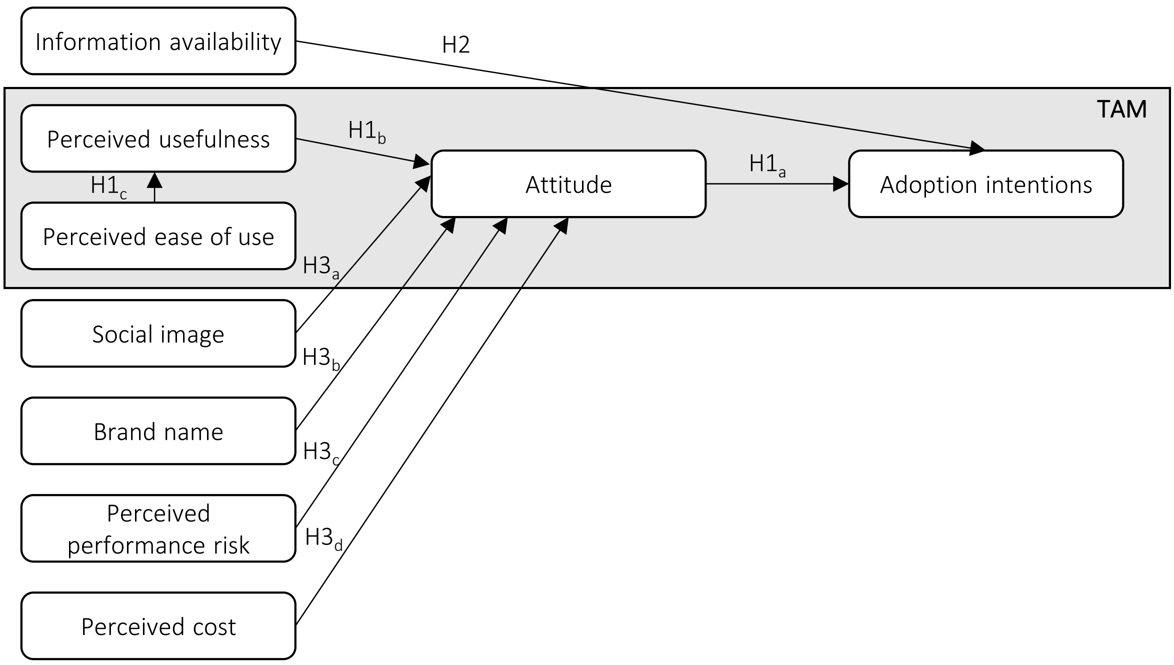

Figure 1. Conceptual model

The study offers the following hypotheses:

H1a: South African youth's attitudes towards SWWs directly influence their adoption intentions.

H1b: South African youth's perceived usefulness of SWWs directly influences their attitudes.

H1c: South African youth's perceived usefulness of SWWs is directly influenced by their perceived ease of use.

H2: South African youth's SWW adoption intentions are directly influenced by information availability.

H3a: South African youth's attitude towards SWW is directly influenced by social image.

H3b: South African youth's attitude towards SWW is directly influenced by device brand name.

H3c: South African youth's attitude towards SWW is directly influenced by perceived performance risk.

H3d: South African youth's attitude towards SWW is directly influenced by perceived cost.

Following the literature overview, rationale, the key gaps identified, and based on prior research, this study proposed the integrated conceptual model shown in Figure 1.

2. METHODOLOGY

The study employed a descriptive research design using a single cross-sectional sample comprising South African consumers who actively participate in parkrun events. A judgment sampling technique was used to select three official parkrun sites located in the Free State and Gauteng provinces. To ensure proportional representation, a non-probability convenience sample of 450 respondents was targeted, with 150 questionnaires distributed at each selected parkrun location.

Prior arrangements were made with local parkrun organizers, and a data collection stand was set up at the event finish lines, where attendees were invited to voluntarily complete the questionnaire. As a community event, it is customary for participants to linger after the event to wait for others, catch up with fellow runners or join group discussions to socialize. Therefore, participants were approached during a relaxed state and not immediately following their intense exercise. This method ensured no negative impact on response quality.

Of 450 questionnaires distributed for the study, 312 were deemed valid and usable for analysis. This resulted in a response rate of approximately 70%, indicating a relatively high level of respondent engagement. The demographic characteristics of the final sample are presented in Table 1, providing insights into respondents' language preferences, provincial distribution, racial groups, gender, and age.

Table 1. Sample's demographic data

Language	Province	Race group
Sesotho: 6.7%	Gauteng: 48.6%	Black: 29.6%
isiZulu: 3.5%	Limpopo: 4.5%	White: 61.8%
Sepedi: 2.6%	Free State: 34.1%	Colored: 5.6%
Setswana: 2.9%	Mpumalanga: 3.2%	Indian/Asian: 2.3%
Afrikaans: 53.8%	North West: 3.2%	Missing: 0.7%
Tshivenda: 2.6%	KwaZulu-Natal: 1.6%	Gender
isiXhosa: 3.8%	Cape (Western): 1.3%	Female: 49.7%
SiSwati: 1.9%	Cape (Eastern): 2.3%	Male: 50.3%
Xitsonga: 0.6%	Cape (Northern):1.3%	Age
English: 20.8%		18-24: 45.5%
Other: 0.3%		25-33: 54.5%

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Table 1 shows that the sample primarily consisted of Afrikaans (53.8%) and English (20.8%) speakers, with most respondents residing in Gauteng (48.6%) and the Free State (34.1%). The majority were White (61.8%), followed by Black (29.6%) respondents. The gender distribution was nearly equal (50.3% male, 49.7% female), and most respondents were between 25 and 33 years old (54.5%), with 45.5% aged 18-24. The sample's characteristics should be considered when interpreting the prediction model.

Data were gathered through a self-administered questionnaire designed to obtain both demographic data and respondents' perceptions regarding wrist-worn fitness trackers across nine predetermined factors. Participation was entirely voluntary and anonymous, with written informed consent secured through a cover letter that outlined the purpose and scope of the research. The informed consent statement read as follows: 'I have read the above description of this research study. I have been informed that it is a low-risk study, and I am aware of the purpose of the study. I voluntarily agree to take part in this study and by continuing and completing this questionnaire, I consent to the information being used in aggregate form'. Data were only gathered after ethical approval from the North-West University's Faculty of Economic and Management Sciences ethics committee (Ethics clearance ref. no: NWU-00097-19-A4).

The questionnaire employed a six-point Likert-type scale, ranging from 1 (strongly disagree) to 6 (strongly agree), to measure the extent of agreement with statements related to each factor. These scales were adapted from previously validated and published sources, namely attitude and adoption intentions (Kim & Shin, 2015; Venkatesh et al., 2003), perceived usefulness (Shin, 2007; Park & Chen, 2007), perceived ease of use (Kim & Shin, 2015; Kuo &Yen, 2009), social image and perceived performance risk (Yang et al., 2016), brand name (Muller, 2019), information availability (Shin, 2012, 2007), perceived cost (Kim & Shin, 2015; Shin, 2009).

Data analysis was conducted using IBM SPSS and AMOS (version 27). Descriptive statistics were computed to summarize the sample characteristics, while reliability and validity measures assessed the internal consistency and construct validity of the scales. Pearson correlations explored relationships between variables, and multicollinearity diagnostics (tolerance and VIF values) were used to evaluate potential collinearity issues. Confirmatory Factor Analysis (CFA) using the maximum likelihood method was performed to validate the measurement model, followed by structural equation modelling (SEM) to examine the hypothesized relationships among the factors.

3. RESULTS

To assess the structure of the component items, Principal Components Analysis (PCA) with varimax rotation was performed. This analysis aimed to detect any cross-loadings and confirm that each item aligned with theoretically established constructs. Before conducting the PCA, the suitability of the dataset was evaluated using the Kaiser-Meyer-Olkin (KMO) measure, which yielded a high value of 0.93, and Bartlett's test of sphericity, which produced a significant result ($\chi^2 = 5836.21$, $df = 351$, $p \leq 0.001$), indicating the data's appropriateness for factor analysis (Pallant, 2020). Table 2 presents the PCA outcomes.

As shown in Table 2, nine extracted components collectively explained approximately 80% of the total variance. No cross-loadings were observed, and the items aligned well with theoretical expectations based on prior research. All communalities exceeded the recommended threshold of 0.40, suggesting that the items within each component shared sufficient common variance (Costello & Osborne, 2005). Moreover, the majority of item loadings were above 0.50, reflecting both statistical and practical relevance (Hair et al., 2019). Overall, the results confirm that the factor structure is consistent with established findings in the literature.

CFA was then conducted using the maximum likelihood estimation method in AMOS. This analysis assessed internal consistency through Cronbach's alpha (α) and composite reliability (CR), while also evaluating convergent, discriminant, and construct validity. To further establish the robustness of the model, various fit indices were examined to confirm both the validity and reliability

Table 2. PCA results

Item	Component									Communality
	1	2	3	4	5	6	7	8	9	
AI1	0.77									0.82
AI2	0.77									0.84
AI3	0.76									0.83
ATT1				0.76						0.80
ATT2				0.72						0.81
ATT3				0.63						0.75
PU1									0.62	0.78
PU2									0.60	0.80
PU3									0.36	0.73
PEOU1					0.83					0.82
PEOU2					0.79					0.79
PEOU3					0.73					0.79
IA1							0.74			0.83
IA2							0.75			0.83
IA3							0.58			0.72
SI1			0.86							0.83
SI2			0.89							0.86
SI3			0.89							0.85
BN1						0.82				0.84
BN2						0.77				0.78
BN3						0.68				0.71
PPR1		0.85								0.82
PPR2		0.82								0.80
PPR3		0.84								0.77
PC1								0.54		0.77
PC2								0.46		0.67
PC3								0.83		0.89
Eigenvalue	11.39	2.56	2.08	1.50	1.28	0.75	0.71	0.66	0.54	
Variance %	42.19	9.49	7.71	5.57	4.76	2.79	2.65	2.43	2.01	

Note: AI = adoption intention; ATT = attitude; PU = perceived usefulness; PEOU = perceived ease of use; IA = information availability; SI = social image; BN = brand name; PPR = perceived performance risk; PC = perceived cost.

of the measurement model. To assess the reliability and validity of the measurement model, several established criteria were applied, as guided by recommendations from Fornell and Larcker (1981), Franke and Sarstedt (2019), Gaskin and Lim (2016), and Almén et al. (2018). Cronbach's alpha (α) values above 0.70 were required to confirm internal consistency. For composite reliability (CR) and convergent validity, CR values needed to exceed 0.70, and the Average Variance Extracted (AVE) had to be at least 0.50. Discriminant validity was evaluated using the heterotrait-monotrait (HTMT) ratio, where values below 0.85 indicated acceptable discriminant validity. Construct validity was further supported by maximal reliability [MaxR(H)] values exceeding 0.70 or the corresponding CR values. The measurement model comprised nine latent constructs, each measured by three observed indicators. Table 3 presents a detailed summary of the reliability and validity assessments.

All latent factors demonstrated strong internal consistency, with Cronbach's alpha values surpassing the recommended threshold of 0.70. CR and convergent validity were also established, as CR values exceeded 0.70 and AVE values were above 0.50. Discriminant validity was supported by HTMT ratios remaining below 0.85. Additionally, construct validity was confirmed, with MaxR(H) values exceeding the minimum benchmark of 0.70.

Once the reliability and validity of the measurement model were confirmed, the analysis proceeded to examine the standardized factor loadings (β), error variances (SMC), and overall model fit. For convergent validity to be supported, standardized loadings were required to exceed 0.50 (Fornell

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Table 3. Measurement model reliability and validity

Latent factor	α	CR	AVE	MaxR(H)	HTMT ratio								
					1	2	3	4	5	6	7	8	9
AI (1)	0.90	0.90	0.76	0.91	–	–	–	–	–	–	–	–	–
ATT (2)	0.87	0.87	0.69	0.87	0.74	–	–	–	–	–	–	–	–
PU (3)	0.81	0.81	0.59	0.81	0.69	0.75	–	–	–	–	–	–	–
PEOU (4)	0.86	0.86	0.67	0.86	0.57	0.58	0.64	–	–	–	–	–	–
IA (5)	0.86	0.86	0.67	0.86	0.60	0.56	0.62	0.55	–	–	–	–	–
SI (6)	0.91	0.91	0.77	0.91	0.25	0.23	0.43	0.26	0.36	–	–	–	–
BN (7)	0.82	0.82	0.62	0.84	0.42	0.41	0.49	0.38	0.66	0.46	–	–	–
PPR (8)	0.86	0.87	0.69	0.88	0.37	0.36	0.39	0.37	0.42	0.27	0.29	–	–
PC (9)	0.80	0.80	0.57	0.81	0.60	0.57	0.56	0.42	0.56	0.26	0.40	0.64	–

Note: AI = adoption intention; ATT = attitude; PU = perceived usefulness; PEOU = perceived ease of use; IA = information availability; SI = social image; BN = brand name; PPR = perceived performance risk; PC = perceived cost.

& Larcker, 1981). Model fit was assessed using a range of indices. A strong model fit was indicated by the following benchmarks: CMIN/DF value between 1 and 3, comparative fit index (CFI) above 0.90, standardized root mean square residual (SRMR) below 0.08, root mean square error of approximation (RMSEA) below 0.06, and PCLOSE value above 0.05 (Gaskin & Lim, 2016). Additional fit indices considered included the relative fit index (RFI), normed fit index (NFI), incremental fit

Table 4. Measurement model estimates and model fit

Latent factor	β	SMC
AI	0.85	0.73
	0.90	0.81
	0.85	0.73
ATT	0.79	0.62
	0.84	0.71
	0.83	0.69
PU	0.76	0.58
	0.76	0.57
	0.79	0.63
PEOU	0.79	0.62
	0.78	0.62
	0.83	0.68
IA	0.85	0.72
	0.85	0.73
	0.76	0.58
SI	0.86	0.75
	0.91	0.83
	0.85	0.73
BN	0.83	0.69
	0.80	0.64
	0.72	0.52
PPR	0.87	0.76
	0.85	0.72
	0.76	0.58
PC	0.82	0.67
	0.73	0.54
	0.72	0.52
Model fit indices	CMIN/DF: 1.80; NFI: 0.90; RFI: 0.91; IFI: 0.95; TLI: 0.94; CFI: 0.96; RMSEA: 0.05; PCLOSE: 0.43; SRMR: 0.04	

Note: AI = adoption intention; ATT = attitude; PU = perceived usefulness; PEOU = perceived ease of use; IA = information availability; SI = social image; BN = brand name; PPR = perceived performance risk; PC = perceived cost.

index (IFI), and Tucker-Lewis index (TLI), with values above 0.90 indicating acceptable fit. A summary of these results is presented in Table 4.

As shown in Table 4, all β values were above the 0.50 threshold, and the measurement model satisfied all the established model fit criteria. These results suggest that the model is both robust and well-specified, making it suitable for further analysis through SEM.

Table 5 presents a summary of the descriptive and preliminary statistical analyses, including the mean ($\bar{X}$), standard deviation (σ), and one-sample t-test results, while Table 6 outlines Pearson correlation coefficients (r) and multicollinearity diagnostics. These analyses were conducted before proceeding with the path analysis. The one-sample t-test assessed whether the latent factors were statistically significant, while Pearson's r was used to examine the strength and direction of the relationships between factors. To evaluate potential multicollinearity, tolerance (TV) and Variance Inflation Factor (VIF) values were calculated.

For each factor, Table 5 reports a statistically significant t-value ($p < 0.001$). The effect sizes (Cohen's d) are all within the range of practical significance (Cohen, 1992). This means that the respondents generally find smart wrist wearables easy to use, and while some respondents consider these devices as status-enhancing or trendy, it is not the primary motivator. Besides, the mean values indicate that the respondents feel that they can easily access information on SWWs, reinforcing potential adoption. The low perceived cost mean score implies that cost is a concern for respondents, as they may view these fitness trackers as expensive or not cost-effective. The respondents generally agree that SWWs produce reliable and consistent health-related metrics and deliver value. Moreover, brand name matters to the respondents, and they may trust or prefer well-known brands such as Apple, Fitbit, Garmin, Polar, and Samsung. Furthermore, the respondents perceive the trackers as useful, meaning they believe the device improves their health or fitness-related goals. Lastly, the respondents report having a positive attitude towards SWWs and a strong adoption intention, which is promising for market growth.

In Table 6, the relationships between the factors are identified, as well as possible multicollinearity.

Table 6 presents Pearson's correlation coefficients, revealing statistically significant positive relationships ($p < 0.01$) among all latent factors, except for perceived cost, which shows negative correlations with the other factors. These findings support nomological validity (Malhotra, 2020), suggesting the relationships between factors align with theoretical expectations. Importantly, none of the correlation coefficients exceed 0.90, indicating that multicollinearity is not a concern (Pallant, 2020). To further confirm this, collinearity diagnostics were conducted using tolerance values (TVs) and Variance Inflation Factors (VIFs), where the average VIF of 2.39 falls well below the critical value of 10, and all TVs exceed 0.10. This confirms that multicollinearity is not a threat to the validity of the analysis (Hair et al., 2019).

Table 5. Summary statistics and one-sample t-test

Latent factor	$\bar{X}$	Σ	t-statistic	p-value	Cohen's d	95% confidence interval	
						Lower	Upper
AI	4.89	0.98	87.81	< 0.001	0.98	4.56	5.37
ATT	4.98	0.90	98.89	< 0.001	0.89	5.14	6.05
PU	4.74	0.90	93.19	< 0.001	0.90	4.84	5.70
PEOU	4.78	0.90	94.20	< 0.001	0.90	4.90	5.76
IA	4.80	0.87	97.74	< 0.001	0.87	5.08	5.98
SI	3.80	1.34	49.99	< 0.001	1.34	2.58	3.08
BN	4.57	1.00	80.63	< 0.001	1.00	4.19	4.94
PPR	4.23	1.14	42.94	< 0.001	1.14	3.40	4.02
PC	2.44	1.00	43.22	< 0.001	1.00	2.22	2.67

Note: AI = adoption intention; ATT = attitude; PU = perceived usefulness; PEOU = perceived ease of use; IA = information availability; SI = social image; BN = brand name; PPR = perceived performance risk; PC = perceived cost.

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Table 6. Relationships between latent factors and collinearity diagnostics

Latent factor	Pearson's product-moment correlation coefficient									Collinearity diagnostics	
	1	2	3	4	5	6	7	8	9	TV	VIF
AI (1)	–	–	–	–	–	–	–	–	–	0.36	2.78
ATT (2)	0.74*	–	–	–	–	–	–	–	–	0.32	3.11
PU (3)	0.69*	0.75*	–	–	–	–	–	–	–	0.30	3.34
PEOU (4)	0.56*	0.58*	0.63*	–	–	–	–	–	–	0.53	1.91
IA (5)	0.60*	0.56*	0.62*	0.55*	–	–	–	–	–	0.38	2.63
SI (6)	0.25*	0.23*	0.43*	0.26*	0.38*	–	–	–	–	0.69	1.45
BN (7)	0.42*	0.41*	0.49*	0.38*	0.66*	0.46*	–	–	–	0.51	1.98
PPR (8)	0.37*	0.35*	0.38*	0.37*	0.42*	0.28*	0.29*	–	–	0.59	1.79
PC (9)	–0.60*	–0.57*	–0.56*	–0.42*	–0.56*	–0.26*	–0.40*	–0.64*	–	0.40	2.49

Note: * Correlation is significant at p < 0.01. AI = adoption intention; ATT = attitude; PU = perceived usefulness; PEOU = perceived ease of use; IA = information availability; SI = social image; BN = brand name; PPR = perceived performance risk; PC = perceived cost.

Table 7. Structural model paths per hypothesis

Hypothesis	Path	Standardized β	Unstandardized β	SE	p	Result
H1a	ATT→AI	0.73	0.86	0.08	0.001	Supported
H1b	PU→ATT	0.78	0.71	0.07	0.001	Supported
H1c	PEOU→PU	0.82	0.82	0.07	0.001	Supported
H2	IA→AI	0.20	0.21	0.06	0.001	Supported
H3a	SI→ATT	–0.11	–0.07	0.03	0.024	Supported
H3b	BN→ATT	–0.01	–0.01	0.04	0.848	Not supported
H3c	PPR→ATT	0.22	0.15	0.05	0.006	Supported
H3d	PC→ATT	–0.47	–0.38	0.08	0.001	Supported

Note: AI = adoption intention; ATT = attitude; PU = perceived usefulness; PEOU = perceived ease of use; IA = information availability; SI = social image; BN = brand name; PPR = perceived performance risk; PC = perceived cost.

The path analysis was then conducted to examine the eight hypothesized relationships outlined in Figure 1. Table 7 presents the outcomes of the structural model, including standardized regression coefficients (β), along with their associated standard errors (SE) and p-values as generated by AMOS. These results provide insight into the strength, direction, and statistical significance of the relationships between the factors within the proposed model.

The path analysis results in Table 7 show that South African youth's perceived usefulness of smart wrist wearables is directly influenced by the technology's perceived ease of use (β = 0.82, p = 0.001, p < 0.01). Moreover, the perceived usefulness of SWWs contributes significantly to their attitude formation regarding this technology (β = 0.78, p = 0.001, p < 0.01), with the compounding effect on the positive association between attitude (β = 0.73, p = 0.001, p < 0.01) and respondents' SWW adoption intentions. These three outcomes support *H1*, *H2a*, and *H3b*, respectively. Interestingly, social image showed a small but significant negative effect on attitude (β = –0.11, p = 0.024, p < 0.05), where, in contrast, perceived cost had a significant negative effect on attitude (β = –0.47, p = 0.001, p < 0.01). Regardless of the polarity of these findings, *H2b* and *H2c* are supported.

In supporting *H2d*, it is evident that South African youth's attitude towards SWWs is significantly in-

Table 8. Structural model fit

Model fit indices							
CMIN/DF	NFI	IFI	TLI	CFI	RMSEA	PCLOSE	SRMR
2.02	0.90	0.97	0.94	0.95	0.05	0.04	0.06

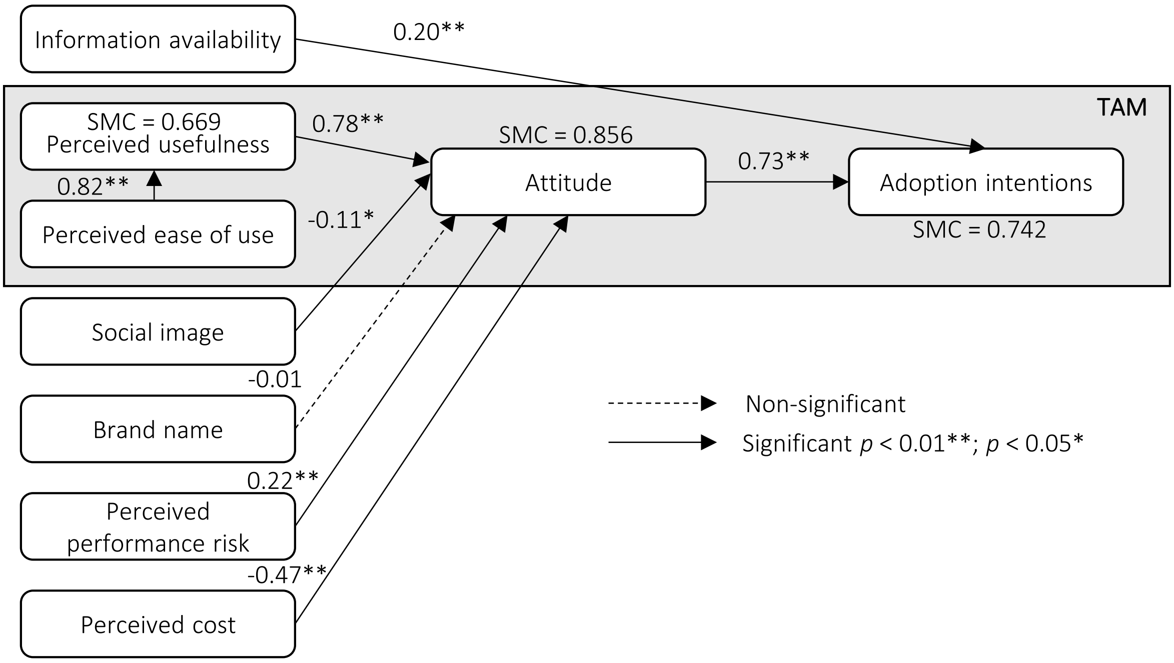

Figure 2. Prediction model for smart wrist wearable adoption among South African youth

fluenced by the perceived performance risk (β = 0.22, p = 0.006, p < 0.01) inherent in using these devices. Furthermore, *H3a* is supported since information availability also positively influences South African youth's SWW adoption intention (β = 0.20, p = 0.001, p < 0.01). In contrast to the latter two findings for perceived performance risk and information availability, often distinguishing factors from leading brands, a reliable brand name (β = –0.01, p = 0.848, p > 0.01) has no significant effect on the respondents' attitude towards SWWs. The lack of support for *H2e* is representative of this study's sample, where further probing might yield different results or uncover the rationale behind this finding.

Squared Multiple Correlations (SMCs) reveal that the structural model accounts for a substantial proportion of variance in the key outcome variables. Specifically, it explains 66.9% of the variance in perceived usefulness, 85.6% in attitude, and 74.2% in adoption intention. These values indicate a strong explanatory power of the model across these latent constructs. A visual depiction of the structural relationships among the variables is presented in Figure 2.

To evaluate the structural model fit, the same set of fit indices applied to the measurement model was utilized. These indices include CMIN/DF, NFI, IFI, TLI, CFI, RMSEA, PCLOSE, and SRMR. The results are outlined in Table 8.

The results, as summarized in Table 8, show that the structural model satisfies all the recommended model fit thresholds, except for PCLOSE, which is marginally below the ideal cutoff value of 0.05. Nonetheless, the overall fit indices indicate a strong and acceptable model fit. Therefore, this study produced a valid and reliable prediction model for smart wrist wearable adoption among South African youth.

4. DISCUSSION

The findings reveal that the structural model is both robust and explanatory, accounting for 66.9% of the variance in perceived usefulness, 85.6% in attitude, and 74.2% in adoption intention. One of the strongest and most consistent findings is the significant positive relationship between perceived ease of use and perceived usefulness, supporting TAM's foundational proposition that the more intuitive and user-friendly a technology is, the more valuable it is perceived to be (Davis, 1989). In the context of this study, youth find SWWs useful in monitoring their activity and health metrics, more so when these devices are easy to use. Similarly, perceived usefulness strongly influenced attitude, and attitude significantly predicted adoption intention, reinforcing existing research that shows ease of use, usefulness and

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consumer attitudes play central roles in shaping consumer acceptance (Chuah et al., 2016; Kim & Shin, 2015; Kuo & Yen, 2009; Muller, 2019, 2022; Park et al., 2016). As such, ensuring the adoption and growth of the SWWs market and successful targeting of South African youth depends on optimizing device ease of use and usefulness.

Unexpectedly, social image showed a small but significant negative effect on South African youth's attitude towards SWWs. This implies that when SWWs are viewed primarily as status symbols, they may reduce favorable attitudes toward this technology. Accordingly, this revelation may reflect a cultural nuance among South African respondents, who may value authenticity, functionality, and personal health benefits over social signaling. One study found the opposite, indicating that young adults do not associate social image with wearable technology usage (Gowin et al., 2019). Leading to further inconsistency regarding the role of social influence is the findings reported by Yang et al. (2016), who reported the indirect importance of wearable technology acceptance mediated by perceived value. Based on the findings, SWW manufacturers, resellers, and marketers must focus on other contributing factors since emphasizing social acceptance is unlikely to convert South African youth.

One significant barrier to address to appeal to price-sensitive youth with marginal disposable income is the associated cost of owning an SWW. This study reveals that perceived cost negatively affects South African youth's attitude, confirming that affordability is a significant barrier to their SWW adoption. This aligns with existing literature, which consistently identifies cost as a limiting factor in technology uptake, particularly in emerging markets (Muller, 2022; Shin, 2009; Yang et al., 2016). Smart wrist wearable brands might convert South African youth without compromising perceived quality using competitive pricing strategies, emphasizing price-value-for-money, introducing reliable devices at different price points, and offering bundled offerings.

Another strategy manufacturers can use to appeal to consumers, specifically those unfamiliar with SWWs, is to emphasize the credibility of the metrics and data produced by their devices. 90% constituting the uncaptured South African market may be hesitant to buy SWWs given the high perceived cost and perceived performance risk. This study reveals that the youth form more favorable attitudes toward SWWs when they believe the devices perform well and produce reliable metrics that they find useful. In line with Yang et al. (2016), who found that lower perceived risk enhances perceived value and subsequently promotes wearable technology adoption, this underscores the crucial role of product quality and technical capability in shaping user perceptions.

Chuah et al. (2016) report the critical role of visibility in wearable technology adoption, which is echoed by the findings of this current study. Accordingly, South African youth are more likely to intend to use SWWs when they are easy to find, purchase, and produce metrics they can access on the device immediately. As such, distribution and SWW accessibility can serve as critical enablers in the technology adoption process, particularly in contexts where consumers rely on both online and physical retail environments for purchasing decisions. Moreover, manufacturing SWWs that allow the user to record and access their activity data immediately might appeal to youth with a need for instant access to information.

Interestingly, brand name did not significantly influence attitude, indicating that brand recognition or loyalty does not play a decisive role in shaping South African youth's attitudes toward SWWs in this context. This contradicts some prior research that emphasizes how consumers rely, largely, on buying a reliable wearable technology brand based on their trust, loyalty, and implied device and data credibility (Dutta et al., 2024; Muller, 2019). Thus, to grow the SWW market by targeting the youth, brands, resellers, and marketers must emphasize practical utility and value rather than prestige or branding.

CONCLUSIONS

This study set out to investigate the key factors influencing South African youth's SWW adoption intention, using an extended TAM in an emerging market context. The results confirm the robustness of the extended TAM in explaining consumer behavior, with perceived ease of use, perceived usefulness, and attitude emerging as central predictors of adoption intention. Information availability and device performance also significantly contributed to positive adoption attitudes, while perceived cost had a notable negative effect. Contrary to expectations, social image negatively influenced attitude, and brand name had no significant impact. These findings highlight context-specific nuances in this study's youth's decision-making and suggest that functionality, affordability, and accessibility are more influential than brand or social appeal among health-conscious South African users.

AUTHOR CONTRIBUTIONS

Conceptualization: Chantel Muller.
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Formal analysis: Chantel Muller, Marko van Deventer.
Methodology: Marko van Deventer.
Project administration: Chantel Muller, Marko van Deventer.
Software: Marko van Deventer.
Visualization: Chantel Muller.
Writing – original draft: Chantel Muller, Marko van Deventer.
Writing – review & editing: Chantel Muller, Marko van Deventer.

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