

The Influence of Online Trends on Consumer Psychology and Purchasing

Decisions in Saudi Customers

تأثير اتجاهات التسوق عبر الإنترنت على نفسية المستهلك وقرارات الشراء لدى العملاء
السعوديين

This thesis is submitted in partial fulfilment of the requirements for the degree of Master of Digital

Marketing

A Quatitative and Exlanatory Study

Prepared by:

Marya Samer Ali Abdullah

Supervised by:

Dr. Mohammed Ewees

2024-2025

Dedication

To my dear parents, who have been there to guide me, strengthened me, and inspired within me every accomplishment I've made. My parents' constant love, sacrifices, also unending prayers have carried me throughout life's obstacles. My siblings and sister-in-law's faith, support, and encouragement in me have filled my adventure with strength and warmth and your love makes everything easier.

And to my beloved partner who has given continues support, patience and love which all have served as my anchor because they all reminded me that I was never alone even at the most difficult times.

This milestone is for all of you with all of my love.

Abstract

This study looks into how Saudi customers' purchase decisions and consumer psychology are affected by online trends. It specifically looks at how psychological factors including motivation, emotional appeal, identity expression, and fear of missing out (FOMO) influence the relationship between exposure to online trends and purchasing decisions. A structured questionnaire was used to gather information from Saudi customers, and Partial Least Squares Structural Equation Modeling (PLS-SEM) was used for analysis. The results show that consumer psychology is greatly impacted by internet trends, and that these psychological processes have a substantial impact on purchasing decisions. Motivation and FOMO were found to be the most important mediators, whereas identity expression and emotional appeal had less of an impact. Additionally, a number of relationships were mediated by demographic factors such as income, employment status, gender, and age. For instance, FOMO had a stronger effect on females, and income levels dictated whether purchases were motivated by identity expression or FOMO. The research adds to the available literature on digital marketing in Saudi Arabia and gives marketers insightful and useful recommendations on how to adapt trend-based tactics to various customer segments.

Keywords: Digital marketing, PLS-SEM, Saudi Arabia, Online trends, Consumer psychology, and Purchase decisions

الملخص

تهدف هذه الدراسة إلى استكشاف تأثير الاتجاهات الرقمية (Online Trends) على علم نفس المستهلك وقرارات الشراء لدى المستهلكين السعوديين. وقد ركزت على العمليات النفسية مثل الخوف من فوات الفرصة (FOMO)، والدافعية، والجاذبية العاطفية، والتعبير عن الهوية باعتبارها متغيرات وسيطة في العلاقة بين التعرض للاتجاهات الرقمية وقرارات الشراء. تم جمع البيانات من المستهلكين السعوديين باستخدام استبيان منظم، وتحليلها من خلال أسلوب النمذجة بالمعادلات الهيكلية (PLS-SEM). أظهرت النتائج أن الاتجاهات الرقمية تؤثر بشكل كبير على العمليات النفسية للمستهلك، والتي بدورها تؤثر بقوة على قرارات الشراء. وقد برز الخوف من فوات الفرصة والدافعية كأهم المتغيرات الوسيطة، بينما كان تأثير الجاذبية العاطفية والتعبير عن الهوية أضعف نسبيًا. كما تبين أن الخصائص الديموغرافية مثل الجنس، العمر، الحالة الوظيفية، مستوى التعليم، والدخل الشهري تعدل بعض هذه العلاقات. على سبيل المثال، كانت الإناث أكثر تأثرًا بالخوف من فوات الفرصة، في حين أن مستوى الدخل حدد ما إذا كانت قرارات الشراء مدفوعة بالخوف من فقدان أو بالتعبير عن الهوية. تسهم هذه الدراسة في إثراء الأدبيات الخاصة بالتسويق الرقمي في السياق السعودي، وتقدم رؤى عملية للمسوقين حول كيفية تصميم استراتيجيات قائمة على الاتجاهات تناسب مختلف فئات المستهلكين.

الكلمات المفتاحية: الاتجاهات الرقمية، علم نفس المستهلك، قرارات الشراء، المملكة العربية السعودية، التسويق الرقمي، PLS-SEM

Table of Contents

<i>Cover Page</i>	<i>1</i>
<i>Dedication.....</i>	<i>2</i>
<i>Abstract</i>	<i>3</i>
<i>List of tables</i>	<i>10</i>
<i>List of Figures</i>	<i>12</i>
<i>List of Abbreviation</i>	<i>13</i>
<i>List of Appendices.....</i>	<i>14</i>
<i>Chapter 1.....</i>	<i>15</i>
<i>INTRODUCTION.....</i>	<i>15</i>
<i>Chapter 2.....</i>	<i>17</i>
<i>LITERATURE REVIEW</i>	<i>17</i>
2.1 The Psychology of Online Trend Influence	18
2.1.1 Social Proof and Herd Behavior	18
2.1.2 Identity Expression and Parasocial Influence	19
2.1.3 Fear of Missing Out (FOMO) and Motivational Triggers	20
2.2 The Influence of Online Trends and Social Media Influencers on Consumer Purchase	
Decisions in Saudi Arabia.....	21
2.2.1 Influencer Credibility and Consumer Trust	21
2.2.2 Local Influencers and Brand Trust	22
2.2.3 Impulse Buying and Trend-Based Purchasing Behavior	23
2.2.4 Cultural Norms and the Localization of Online Trends	23
2.2.5 The use of Micro vs. Macro Influencers	24
2.2.6 Impact of social media influencers on Saudi consumers purchase intention	25

2.3 Digital Marketing Strategies Leveraging Online Trends	26
2.3.1 Real-Time Marketing and Trend jacking.....	26
2.3.2 AI and Data Analytics in Trend-Targeted Campaigns	27
2.3.3 Personalization Based on Trending Interests	28
2.4. Synthesis and Critical Reflection	29
2.5 Problem statement	30
2.6 Research objectives	31
2.7 Research Questions	32
2.8 Key Concepts of the Study	33
2.8.1 Online Trends.....	33
2.8.2 Consumer Psychology	33
2.8.3 Purchasing Decisions	33
2.8.4 Fear of Missing out (FOMO)	34
2.8.5 Real-Time Marketing.....	34
2.8.6 Trend jacking.....	34
2.8.7 Influencer Marketing.....	35
2.9 Theoretical Development	35
2.9.1 Independent Variables	36
2.9.2 Mediating Variables	36
2.9.3 Moderating Variables.....	37
2.9.4 Dependent Variable.....	37
2.10 Hypothesis Development	37
2.10.1 Hypothesis	38
2.11 Theoretical Framework	38
<i>Chapter 3</i>	<i>41</i>
<i>Research Methodology.....</i>	<i>41</i>
3.1 Research Design	41
3.2 Population and Sampling	41

3.3 Data collection method.....	42
3.4 Scope of Study	42
3.5 Instrument development and design	42
3.6 Validity and Reliability	43
3.7 Questionnaire Data Analysis	45
<i>Chapter 4 Results and Discussion.....</i>	<i>47</i>
4.1 Introduction	47
4.2 Pilot Study Readings.....	48
4.2.1 Construct Reliability and Validity Results.....	49
4.2.2 HTMT analysis for Discriminant validity.....	49
4.3 Frequency Distribution	51
4.4 Data Screening.....	53
4.5 Respondent profile	54
4.5.1 Gender.....	54
4.5.2 Age	56
4.5.3: Education Level of Respondents	57
4.5.4 Monthly Income	58
4.5.5 Employment Status	59
4.5.6 Summary of Respondent Profile	60
4.6 Descriptive Statics of Constructs	60
4.6.1 Costruct Mean Exposure to Online Trends (EOT)	62
4.6.2 Construct Fear of Missing Out (FOMO)	62
4.6.3 Construct Motivation (MOT)	62
4.6.4 Construct Emotional Appeal (EA)	62
4.6.5 Construct Identity Expression (IE).....	63
4.6.5 Purchase Decision (PD)	63
4.6.6 Summary	63
4.7 Evaluation of PLS path model results	64
4.8 Assessment of Measurement Model.....	67

4.8.1 Indicator Reliability.....	67
4.8.2 Internal Consistency Reliability	68
4.9 Construct Reliability and Convergent Validity	69
4.10 Assessment of Discriminant Validity	70
4.10.1 Fornell-Larcker criterion	70
4.10.2 Cross-Loadings	71
4.10.3 Heterotrait-Monotrait Ratio (HTMT).....	73
4.11 Moderation Analysis: Demographic Characteristics	74
4.11.1 Moderation by Gender	74
4.11.2 Moderation by Age	76
4.11.3 Moderation by Education Level.....	78
4.11.4 Moderation by Employment Status	79
4.11.5 Moderation by Monthly Income	82
4.12 Hypothesis Testing.....	83
4.13 Chapter Conclusion.....	87
<i>Chapter 5.....</i>	<i>89</i>
<i>Discussion and Conclusion</i>	<i>89</i>
5.1 Introduction.....	89
5.2 Discussion of Hypotheses and Research Objectives	90
5.2.1 Hypothesis 1 and Objective 1	90
5.2.2 Hypothesis 2 and Objective 2	90
5.2.3 Hypothesis 3	91
5.2.4 Hypothesis 4 and Objective 3	92
5.2.5 Hypothesis 5	94
5.3 Theoretical Implications	94
5.4 Practical Implications.....	95
5.5 Limitations of the Study.....	95
5.6 Recommendations for Future Research	96
5.7 Conclusion	96

<i>References.....</i>	<i>97</i>
------------------------	-----------

<i>APPENDIX A.....</i>	<i>102</i>
------------------------	------------

List of tables

<i>Table 3. 1: 5-point Likert Scale Format</i>	43
Table 3. 2: Cronbach's Alpha (α) values	45
Table 4. 1: Presents the construct reliability and validity results.	49
Table 4. 2: Heterotrait-Monotrait Ratio (HTMT).	51
Table 4. 3: Demographic Profile of Respondents.	52
Table 4. 4: Summary of processed questionnaire responses.	53
Table 4. 5: Gender Distribution of Respondents.	54
Table 4. 6: Age Group of Respondents.	56
Table 4. 7: Education Level of Respondents.	57
Table 4. 8: Monthly Income of Respondents.	58
Table 4. 9: Employment Status of Respondents.	59
Table 4. 10: Descriptive Statistics of Constructs and Items.	61
Table 4. 11: Path Coefficients, T-Statistics, and Significance Levels of the PLS-SEM Model.	65
Table 4. 12: PLS-SEM R-Square Table.	66
Table 4. 13: Outer Loadings of Measurement Model Indicators.	68
Table 4. 14: Internal Consistency Reliability of Constructs.	68
Table 4. 15: Reliability and Convergent Validity.	69
Table 4. 16: The Fornell-Larcker criterion.	71

Table 4. 17: Cross-Loadings of Indicators for Assessment of Discriminant Validity.	72
Table 4. 18: HTMT Ratios for Discriminant Validity.	73
Table 4. 19: Interaction Effects of Gender on Mediator → PD Paths.	75
Table 4. 20: Conditional Effects of FOMO → PD by Gender.	75
Table 4. 21: Regression Results for Effects of EOT and Age Group on Mediators (PROCESS Model 7)...	77
Table 4. 22: Conditional Indirect Effects of EOT on PD via Mediators at Age Groups.....	77
Table 4. 23: Conditional Indirect Effects of EOT on PD by Education Level.....	79
Table 4. 24: Conditional Indirect Effects of EOT on PD for Students.	81
Table 4. 25: Conditional Indirect Effects of EOT on PD for Employed.....	81
Table 4. 26: Conditional Indirect Effects of EOT on PD for Unemployed.	82
Table 4. 27: Moderation of Income on Psychological Processes Predicting PD.....	83
Table 4. 28: Hypothesis testing findings.....	86

List of Figures

Figure 1: Proposed Theoretical Framework.....	40
Figure 2: Gender Distribution of Respondents.	54
Figure 3: Age Distribution of Respondents.	56
Figure 4: Educational level of Respondents.	57
Figure 5: Monthly Income of Respondents.....	58
Figure 6: Employment Status of Respondents.	59
Figure 7: PLS-SEM Structural Model Results (SmartPLS Output).....	65

List of Abbreviation

OT – Exposure to Online Trends

PD – Purchase Decision

FOMO – Fear of Missing Out

MOT – Motivation

EA – Emotional Appeal

IE – Identity Expression

S-O-R – Stimulus–Organism–Response

PLS-SEM – Partial Least Squares Structural Equation Modeling

CI – Confidence Interval

SE – Standard Error

LLCI – Lower Limit Confidence Interval

ULCI – Upper Limit Confidence Interval

SPSS – Statistical Package for the Social Sciences

List of Appendices

A – Survey questionnaire

Chapter 1

INTRODUCTION

The rise of online trends such as TikTok aesthetics, influencer campaigns, viral challenges, memes etc., has transformed the way consumers choose what to buy and how to connect with brands. Usually coming from sites like TikTok, Instagram, and YouTube, online trends are fast moving, culturally popular ways of acting and sharing content. These trends can often mix entertainment with more persuasive communication and are used to grow brand visibility by memes, challenges, and influencer visuals (Wang, 2024).

Globally, online trends have greatly changed marketing plans by increasing user involvement, shared creation, and instant connection. This move has changed how consumers connect because it values being real and including people over standard ads (Diallo et al., 2021). Trust as well as loyalty are powered via digital engagement within a worldwide shift during customer-brand exchanges noted by (Alfalih, 2022). So, marketing changed over time from broadcasting into conversation and went through changes from convincing to joining in (Grewal, 2024).

In this digital age, online trends have not only been a wave of entertainment but also emerged as powerful drivers about consumer behavior particularly using platforms like TikTok, Instagram, Snapchat, X, also YouTube globally and locally (Wang, 2024).

Khan et al., (2021), in his study stated that one of the highest rates of social media use worldwide is seen in Saudi Arabia, and because its populace is youthful and tech-savvy, online trends are

significantly relevant there. Moreover, the Kingdom's Vision 2030 transformed digitally rapidly also opened up to global consumer cultures, which impacted the local market's online trends faster. Increasingly, it has been shown that the psychological responses and purchasing decisions of Saudi consumers has been shaped by user-generated content, viral marketing, and global influencers lately (Abdulaziz et al., 2023).

Building on previous research, this research aims to explore how online trends affect consumer psychology and influence purchasing decisions with Saudi consumers.

Chapter 2

LITERATURE REVIEW

The rapid growth of digital platforms along with social media has greatly transformed consumer behavior because online trends now shape consumer psychology plus purchasing decisions, particularly in the Saudi market. Given that consumers do rely more and more on social media when it comes to information and inspiration, trends can spread with speed and have influence upon perceptions, preferences, and upon buying patterns. Marketers must have a comprehension of all of the psychological mechanisms that are behind this influence. They should also understand the role of various social media platforms and the unique characteristics of Saudi consumers if they seek to leverage these trends effectively. This literature review explores these dynamics via four key themes:

1. The psychology of online trend influence
2. The Influence of Online Trends and Social Media Influencers on Consumer Purchase Decisions in Saudi Arabia.
3. Real-Time Marketing and Trend jacking
4. Synthesis and Critical Reflection

2.1 The Psychology of Online Trend Influence

This theme examines the psychological mechanisms by which consumer behavior is shaped through online trends, particularly with respect to decision-making, emotional response, motivation, and also perception. These constructs for this discussion include social proof, fear of missing out (FOMO), emotional triggers, and identity-based engagement, and they are key too. These constructs engage with identity then trigger emotion due to FOMO and social proof. These factors largely influence how consumers especially in digitally active environments respond to rapidly changing trends on social media platforms.

2. 1.1 Social Proof and Herd Behavior

Md Shakir Ali et al., n.d. (2025), "**The Power of Social Influence in Consumer Choices**".

This research provided valuable perceptions into consumer decision-making via focusing on the roles of social proof along with herd behavior in the psychology of online trend influence. Ali et al. stated that social proof operates when people mimic what others do in ambiguous situations by relying on reviews they find online, how customers rate products highly, and what customers say in testimonials, which greatly increase trust to purchase and convert leads while, Herd behavior is something that complements this because it describes just how consumers will follow the majority for the reason that they need social acceptance, or, they fear missing out (FOMO), particularly when it comes to trending products that are in fast-moving sectors such as fashion and also technology. That social proof and herd behavior correlate

strongly to purchasing decisions is confirmed by the study and based on this fact, they are very importance in digital marketing strategies. A quantitative method was employed and a survey distributed to the targeted respondents and 150 respondents data was collected in Karnal and Hisar, India, using structured questionnaires. Data analysis involved descriptive statistics, correlation, regression, and Chi-square tests. Md Shakir Ali et al., n.d., (2025) found that Social influence significantly affects purchasing behavior.

2.1.2 Identity Expression and Parasocial Influence

Sarkis et al., (2024),"Examining influencer marketing: the roles of para- social relationships, unpaid collaborations, and trustworthiness in shaping consumer buying behavior"

Another psychological mechanism influencing consumers' responses to online trends is the role of digital identity and self-expression. Researchers in this study investigated how identity expression and online consumer behavior are influenced by para-social interactions and relationships, which are one-sided emotional bonds that consumers or audience form with influencers using online media despite having no real social interaction with them as defined by (Donald Horton & R. Richard Wohl, 1956). In the context of Lebanon, Sarkis et al., (2024), found that Lebanese consumers often form close bonds with influencers, gaining inspiration from their lifestyle and adapting their purchases accordingly. This study used a quantitative method with an online questionnaire using 5-point Likert scale and was distributed to 250 Lebanese respondents. Results from this study confirmed the assumption that customers express their identities by following influencers they trust, love and follow showing that these interactions

considerably increase trust and purchase intentions. As a result, the study showed that para-social influence is one of the main psychological processes influencing the acceptance of online trends and the development of identities in digital contexts.

2. 1.3 Fear of Missing Out (FOMO) and Motivational Triggers

Moore & Craciun, (2021), "**Fear of Missing Out and Personality as Predictors of Social Networking Sites Usage: The Instagram Case.**"

This study offered key insights into the psychological mechanisms driving online trend influence, particularly through Instagram. Also, the concept of Fear of Missing Out (FOMO) has also been shown to significantly affect consumer motivation and engagement with trendy online content. This study focused on Instagram users and found that FOMO was a key driver of user interaction with influencer-generated content. Moreover, this psychological state was linked to both increased product engagement and decreased subjective wellbeing. Also, FOMO served as a mediating factor between social media exposure and consumer action, particularly in promoting time sensitive or trend based purchases. (Moore & Craciun, 2021), in this study aimed to gain more accurate and comprehensive insights thus, chose a mixed method approach involving both surveys and behavioral data collection. The main findings of this study showed that FOMO not only encourages consumer activity but also operates as a behavioral accelerator causing faster and less deliberative decision making.

2. 2 The Influence of Online Trends and Social Media Influencers on Consumer

Purchase Decisions in Saudi Arabia

In the age of digital hyper connectivity, online trends and social media influencers have emerged as powerful forces that shape consumer behavior specifically in Saudi Arabia's increasingly digital marketplace; this is because trend-driven consumption is simultaneously becoming a dominant behavioral pattern among Saudi consumers. Also, influencers on platforms such as TikTok, Instagram and Snapchat are key links between the consumer choice and the fast-moving online trends. Therefore, this theme is structured around six sub-themes to explore how these 2 phenomena co-shape consumer purchase decisions in the Saudi market.

2.2.1 Influencer Credibility and Consumer Trust

Saad et al., (2025), "**Influencer marketing's impact on credibility and purchase intention: A study on University of Bisha students in Saudi Arabia**"

This research studied the very influential role that social media influencers play in the shaping of purchasing intentions particularly among young consumers in Saudi Arabia at the University of Bisha. They found out that Influencer credibility defined by content quality, attractiveness and trustworthiness improved consumer trust and purchase intention significantly. Saad et al., (2025), in this study used a descriptive-analytical methodology and examined the effects of influencer marketing on brand credibility and purchase intention among 384 male and female students at the University of Bisha, in Saudi Arabia using a structured online and in-person survey across various faculties. They found out that

influencer credibility not only affects purchase intention directly, but it also works as a partial mediator since it increases how influencer traits affect consumer choices. Besides, they found out that what strengthen this trust between influencers and the audience is endorsements transparency and cultural alignment. As a result, ensuring deep resonance within the target audience causing effective purchase behavior and building trust on credible influencers who aligns with their followers' values and social norms.

2.2.2 Local Influencers and Brand Trust

Alanmi & Alharthi, (2023), "**The Impact of Digital Marketing on Consumer Buying Behavior in Saudi Arabia: Brand Popularity as a Mediator**".

This study investigated how digital marketing, specially via social media channels like Snapchat, TikTok, and Twitter, influences consumers' purchase decisions, buying habits, and brand recognition in Saudi Arabia. Using a quantitative method, the researchers collected data from 200 local social media users through online questionnaires and analyzed the results using SPSS. They found that digital marketing has a important and positive influence on both consumers buying behavior and purchasing decisions. Also, brand popularity mediates these relationships. These findings suggested that local influencers and interactive campaigns can promote brand trust by increasing brand popularity and directing consumer decisions as a result. The study highlighted that organizations should prioritize digital marketing strategies to strengthen brand trust and expand their customer base in the local context.

2.2.3 Impulse Buying and Trend-Based Purchasing Behavior

AL Hilal, (2023), **"The Impact of the Use of Augmented Reality on Online Purchasing Behavior Sustainability: The Saudi Consumer as a Model."**

AL Hilal, (2023), in this study explored how augmented reality (AR) which is a trend driven technology affects online purchasing behavior among Saudi consumers. This study used a descriptive and analytical quantitative methodology and surveyed (812) AR users through a validated questionnaire, focusing on AR factors and dimensions based on the Technology Acceptance Model and Ihde's theory of intermediate technology. The findings revealed a strong positive correlation between AR dimensions such as the purchasing experience, quality, satisfaction, and creativity, with women and married respondents expressing more favorable attitudes. Moreover, this study found that AR's impact was especially notable in the apparel and accessories sectors. The study also revealed that AR-enabled virtual try-ons enhanced the sense of product realism, leading to higher purchase intention, especially among young Saudi women. These findings show that emerging digital experiences increase the impulsive buying behavior by increasing emotional engagement and product confidence.

2.2.4 Cultural Norms and the Localization of Online Trends

Bahaddad, (2021), **The Traditional Influence on Increasing Acceptance of Commercial Smartphone Applications in Specific Regions of the Arabic World**

This study investigates how cultural norms shape the adoption of commercial smartphone applications in Saudi Arabia, UAE, and Qatar. The researchers employed online questionnaires

distributed to 799 participants familiar with e-commerce. Statistical analysis highlighted both widely shared needs and notable differences across the countries. Key findings revealed that while some application features are globally valued, cultural differences such as preferences for color use, language options, content presentation, and feedback channels significantly affect user acceptance. These findings highlights the necessity of localized customization in commercial app design, confirming that successful M-commerce adoption in the Arabic Gulf depends on aligning features with community-specific traditions and expectations.

2.2.5 The use of Micro vs. Macro Influencers

Kay et al., (2020), "**When less is more: the impact of macro and micro social media influencers' disclosure**"

Social media influencers are usually categorized into those micro-influencers that typically have fewer than 100,000 followers and also those macro-influencers that often are exceeding one million followers. Therefore, Kay et al., (2020), in this research aimed to find out whether type of influencers—micro or macro—are more convincing and the effectiveness of different influencer types and the impact of sponsorship disclosure on marketing outcomes. Thus, this study examined the way that the type of influencer and the presence of sponsorship disclosure have an effect on consumer responses which included product knowledge, perceived attractiveness, and purchase intention. The research used of a 2x2 experimental design with a total of 334 female Instagram users who were interested in beauty products, and the research varied by influencer popularity plus sponsored content visibility. The results

showed that Micro-influencers improved consumers' product knowledge beyond macro-influencers and consumers' purchase intent was also shown to improve because of the results.

Furthermore, because sponsorships were disclosed, both the perceived attractiveness of the product and purchase likelihood were positively influenced. Purchase intention was at its highest point among micro-influencers who did notably disclose sponsorships. These findings stress the effectiveness of smaller-scale influencers as well as the value of transparency in influencer marketing because they suggest that "less is more" may be a planned approach in digital campaigns.

Online trends are becoming major drivers of consumer behavior due to the quick increase in digital connection and the domination of social media platforms. Trend driven consumption, in which perceptions and purchase decisions are influenced by influencers, visual marketing, and platform-specific features such as Reels, has been adopted by Saudi Arabia's digitally engaged population, particularly the youth. This theme examines the ways in which these internet changes impact Saudi customers' purchase decisions, with a particular emphasis upon cultural influences, psychological triggers, and digital trust mechanisms in three sub-themes.

2.2.6 Impact of social media influencers on Saudi consumers purchase intention

Nasser Al et al., (2020), "Effect of social media influencers on purchase intentions of Saudi Arabia consumers: Instagram as an evaluation tool".

This study explored the significant influence of social media influencers (SMIs) on the purchase intentions of Saudi Arabian consumers particularly, with a specific focus on Instagram as an evaluation tool. The research highlighted how influencer marketing using credible, persuasive, and professional individuals drives greater consumer engagement, product trust, and as a result, purchase intent. By using Instagram as a case study, the study employed a qualitative literature review method to conceptually explore how social media influencers affect purchase intentions in the Saudi market and the results showed that SMIs impacts Saudi consumers' purchasing decisions significantly through increased trust, credibility and engagement highlighting the role of Instagram in modern digital marketing strategies in the context of Saudi Arabia

2.3 Digital Marketing Strategies Leveraging Online Trends

This theme explores how companies utilize online trends as part of their digital marketing strategies to influence Saudi consumers and drive purchasing behavior. The studies reviewed examine the integration of AI, real-time analytics, and content personalization to enhance marketing outcomes in trend-sensitive environments.

2.3.1 Real-Time Marketing and Trend jacking

Aalijah, (2025), **"Utilizing Social Media Analytics to Detect Trends in Saudi Arabia's Evolving Market"**.

This study investigates how AI-driven social media analytics allow for the real-time tracking of market trends in Saudi Arabia to assist tactics like trend-jacking and real-time marketing. The researcher used a method that combines Natural Language Processing (NLP) models to analyze more than 30 million postings from Facebook, Instagram, TikTok, and X. After preprocessing the data, the researchers analyzed sentiment. To cluster trends, they employed advanced topic modeling. Trend trajectories and sentiment with engagement levels, and growth indicators were all predicted by the Prophet forecasting model. Key findings revealed rising trends in digital transformation, economic diversification, and sustainability, while topics like oil dependency declines, showing how real-time analytics can inform personalized business and marketing strategies in dynamic markets.

2.3.2 AI and Data Analytics in Trend-Targeted Campaigns

Alotaibi et al., n.d., (2025), "**Artificial Intelligence, Big Data, and Their Impact on Improving Marketing Effectiveness and Customer Experience in the Retail Sector in the Kingdom of Saudi Arabia**".

Marketers use AI as well as data analytics to act on also to gather, then to interpret trend and sentiment data's large volumes. This capability let brands anticipate what consumers prefer and design strategies for proactive campaigns accordingly. Therefore, Alotaibi et al., n.d., (2025), wanted to investigate how Artificial Intelligence (AI) and Big Data technologies impact the customer experience and marketing performance within the Saudi retail sector. The researchers used a qualitative methodology, and interviewed 20 experts in and semi-structured interviews from the Saudi retail and marketing sectors

to investigate the integration of Artificial Intelligence (AI) and Big Data in trend-targeted campaigns. Thematic analysis also revealed AI and data analytics greatly improve marketing effectiveness since they allow exact consumer targeting plus campaign personalization. Also, AI and data analytics do predict marketing strategies. Furthermore, participants highlighted return on investment went up, costs were cut, as well as campaign accuracy improved. Moreover, the study showed that both automated and tailored recommendations improved consumer engagement, resulting in higher customer satisfaction and longer client retention.

2.3.3 Personalization Based on Trending Interests

Binlibdah, (2024), **"Investigating the Role of Artificial Intelligence to Measure Consumer Efficiency: The Use of Strategic Communication and Personalized Media Content"**.

This research studied how artificial intelligence (AI) improves personlization in digital marketing ocusing on trending consumer interests. In the study, quantitative method was followed by distributing survey to Saudi Arabian social media users who were active users and collecting 367 valid replies. The links between strategic communication, tailored media content, and customer service efficiency were analyzed using structural equation modeling (SEM) in Smart PLS 4 software. This study found that personalized media content by itself does not immediately increase customer service efficiency, despite the fact that strategic communication promotes both personalized content and service efficiency. Rather, AI completely mediates this relationship, enabling personalized approaches to successfully enhance

results by adjusting to changing customer preferences, highlighting AI's critical position in real-time personalization and customer engagement.

2.4. Synthesis and Critical Reflection

The reviewed literature highlights how online trends dynamically blend with consumer psychology as well as purchasing behavior, especially within the Saudi digital landscape. Psychological factors such as social proof, fear of missing out (FOMO), and identity expression greatly affect consumer responsiveness to online trends, as the first theme portrayed Md Shakir Ali et al., n.d.; Moore & Craciun, (2021). Cognitive and emotional drivers shape behavioral intentions because influencer marketing reinforces parasocial relationships and perceived authenticity (Kay et al., 2020; Saad et al., 2025).

The second theme stressed upon the critical role that social media platforms have. These platforms act as incubators of trends along with behavior-modifying content. Platform algorithms, engagement features such as Instagram Stories and Reels along with AR filters can mediate consumer attention, shape preferences as revealed through studies such as (AL Hilal, 2023; -Nasser Al et al., 2020)

The third theme addressed people's transition from trend awareness and engagement to real purchasing. Additionally, localized marketing strategies and cultural alignment convert attention into buying action particularly among Saudi Arabia's younger demographics, according to (Alanmi & Alharthi, 2023; Bahaddad, 2021).

Finally, the fourth theme examined how businesses utilize online trends via personalization, real-time data, and AI-powered marketing tools. Marketers can use advanced analytics for prediction of trends then adjust campaigns based on that accordingly and close that gap existing between digital engagement with business performance as noted by (Aalijah, 2025; Alotaibi et al., n.d.; Binlibdah, 2024).

Even with researchers finding richness, gaps still exist there. Few of the studies do integrate the technological, the cultural, and the psychological dimensions. Notably, a uniform model lacks these particular areas. Research remains limited regarding Saudi consumers interpreting trend content and adopting trend content especially in emotionally driven or impulsive contexts for daily decisions. Moreover, with AI and data analytics being cited frequently as tools of influence, their indirect psychological impacts on consumers also remain underexplored.

This thematic review is highlighting a holistic approach with a blending of real-time marketing strategy and cultural specificity and consumer psychology. This study now seeks to fill these gaps since it explores how trend-based marketing shapes consumer perceptions and choices in Saudi Arabia, which provides both theoretical perceptions and practical implications for digital marketing professionals.

2.5 Problem statement

In recent years, Saudi Arabia's younger population has displayed sharp increases in internet usage plus social media activity. Saudi consumers find influencer aesthetics and trend-driven content very effective especially younger ones (ALNefaie, 2019). This shift has led toward increased exposure to

online trends including influencer marketing, viral product promotions, also user-generated content. These digital phenomena are reshaping consumer attitudes and also emotions and decision-making processes (Suri, 2023). These effects are occurring in ways still not fully understood. Although, global research has explored the impact of online trends upon consumer behavior. Psychological influences such as fear of missing out (FOMO), social proof, and emotional appeal play a role, but their specific impact remains unclear on Saudi consumers which may be uniquely shaped by cultural elements such as social norms, religious values, and family expectations.

While global studies have already explored the psychological effects of trends and their impact on purchasing decisions, Marketers, retailers, and policymakers risk missing key perceptions into how digital trends influence consumption in the Saudi market if they do not clearly understand these dynamics. Furthermore, the role of AI, trend personalization, and local influencer culture in influencing consumer psychology remains underexplored. This knowledge gap makes it challenging for marketers to design culturally relevant and psychologically effective campaigns targeting Saudi consumers and this study is aiming to fill this gap.

2.6 Research objectives

The objective of this study is to look into the decisions of purchasing as well as the psychology of the consumer among consumers who are Saudi through online trends. Here are the main objectives of this study:

1. To examine psychological factors, like, perception, emotion, motivation, influenced by online trends within the Saudi market.
2. To analyze how Trends like; influencer marketing, viral content, viral products and user-generated content impact and shape Saudi consumers' purchasing behavior.
3. To explore how cultural or demographic variables like age, gender, or religiosity moderates the relationship between online trends with consumer decisions.

2.7 Research Questions

1. How do online trends influence Saudi consumers' psychological processes such as motivation, perception and emotion?
2. What psychological mechanisms (FOMO/emotional appeal/identity expression) are triggered by online trends among Saudi consumers?
3. How does different demographic groups such as age, gender, or education level responses to online trends among Saudi consumers?

2.8 Key Concepts of the Study

2.8.1 Online Trends

According to (Granstedt, 2024), online trends are any viral digital content, topics or even behaviors that spreads quickly over platforms impacting the audience behavior and perception. These trends including memes, challenges, influencer campaigns, trending sounds and hashtags usually starts on social media platforms such as TikTok and Instagram.

2.8.2 Consumer Psychology

Consumer psychology is the exploration of consumer's attitudes, perceptions, behavior and motivation in relation to consumption activities (Mandung et al., 2024).

2.8.3 Purchasing Decisions

As per (Antosova et al., 2023), purchasing decision is a result of complex procedure which consumers go through and get influenced by emerging and traditional factors when deciding whether to purchase a product or service.

2.8.4 Fear of Missing out (FOMO)

(Moore & Craciun, 2021), defined the concept of Fear of Missing out (FOMO) as a widespread fear someone would feel that others may be enjoying fulfilling experiences while they are not. In their study, Moore & Craciun, (2021) characterized FOMO by dissatisfaction, anxiety and frustration. Fear of missing out (FOMO) is experienced by individuals who are exposed to social media platforms like TikTok and Instagram as such platforms provides constant chances for social interaction allowing individuals to keep track of others experiences and activities.

2.8.5 Real-Time Marketing

As per Duarte & Paulo (2023), Real-Time Marketing is how brands rapidly respond to current trends, events or cultural occasions with relevant content. Real-Time marketing as a strategy seeks to actively engage the audience through connecting a brand's message to the current and trending happenings to seem more relevant, relatable and up to date.

2.8.6 Trend jacking

Farys, Harrison (2025), referred to Trend jacking as the practice of influencers or brands of using current trends to increase the audience engagement and brand recognition frequently in real-time on social media. This happens because influencers use trending and viral products to grab attention, Trend jacking has the ability to boost consumers interest and encourage them towards making purchases

2.8.7 Influencer Marketing

Influencer marketing is a very important component of digital marketing (Saad et al., 2025). This marketing strategy uses social media influencers to endorse and promote products, services and brands. Influencer marketing serves as an expansion to the traditional word-of-mouth marketing strategy, it connects and influences consumers using the wide reach of digital platforms.

2.9 Theoretical Development

In theoretical research frameworks, independent and dependent variables are often used to explore relationships between influencing factors and behavioral outcomes. In this study, the independent variables are online trends and their components (such as FOMO, influencer marketing, personalization, and trend jacking). These influence the dependent variable, which is in this research the Purchasing decisions of Saudi consumers.

According to (Saunders et al., 2020), the independent variable is the factor that can be manipulated or observed as the cause, while the dependent variable is the response or outcome that is influenced. Mediating variables serve to clarify the mechanism through which the independent variables exert influence on the dependent variable, which in this case is the consumer psychological processes which acts as mediating variables, helping explain how online trends affect final purchasing behavior. Moreover, demographic variables like age, gender, and level of education serve as moderating factors, affecting the path and strength of the correlation between online trends and behavioral or psychological outcomes.

2.9.1 Independent Variables

Independent variables in this research are core elements of online trends, they show how Saudi digital consumer environments apply online trends:

- **FOMO (Fear of Missing Out):** The pressure created by temporary digital trends drives impulsive purchasing.
- **Trend-based Personalization:** Customized marketing content based on new digital interests.
- **Social Media Influencers:** Influence brand trust and trend-following behavior.
- **Real-time Marketing and Trend jacking:** Brands aligning with current events or viral content to engage audiences.

2.9.2 Mediating Variables

The impact of online trends on buying decisions is mediated by consumer psychological processes. These mediators are essential for understanding the psychological processes that link trend stimuli to consumer behavior and they consist of:

- **Motivation:** Online trends drive aspirational and pleasure-seeking motives.
- **Perception:** Trend relevance and social validation are the two main lenses through which consumers interpret marketing messaging.
- **Emotion:** Decisions are greatly influenced by emotional reactions like belonging, excitement, and anxiety.

2.9.3 Moderating Variables

- **Demographic Factors (Age, Gender, Education):** These factors affect the degree to which people are affected by online trends. For instance, women may interact with influencer content differently than males, and Gen Z customers may be more trend-sensitive than older consumers.

2.9.4 Dependent Variable

The dependent variable is:

- **Consumer Purchasing Decision:** This is a reflection of how exposure to trend-driven content influences behavioral outcomes including brand choice, intention to buy, and actual purchasing.

2.10 Hypothesis Development

In light of the increasing influence of online trends and personalized content on consumer behavior, digital marketing is rapidly changing in the Saudi context (Aalijah, 2025). According to the literature, exposure to digital trends has a positive and strong impact on consumer psychology, which in turn influences purchasing behavior. Numerous academics have shown how online trends work as triggers for behavior, stimulating psychological processes like social proof and FOMO, especially in younger Saudi consumers who are accustomed to using technology (Binlibdah, 2024; Faqihi et al., 2024; Saad et al., 2025). Based from the literature on consumer behavior and psychology, the following hypotheses are proposed:

2.10.1 Hypothesis

H1: Online trends have a strong and positive effect on Saudi consumers' psychological processes.

H2: Consumer psychological processes mediate the relationship between online trends and consumer purchasing decisions.

H3: Online trends have a significant and positive direct effect on consumer purchasing decisions.

H5: Demographic factors including age, gender, and level of education have significant effects on how online trends affect consumer psychology.

H6: Demographic characteristics moderates the influence of psychological processes on purchasing decisions.

2.11 Theoretical Framework

This study will adopt the Stimulus—Organism—Response (S-O-R) model which was firstly presented by Mehrabian, (1974) who is an environmental psychologist. This model explains how a person's internal behavior and emotions are influenced by external environmental stimuli which as a result leads to behavioral responses. This model consists of three main components which are:

- **Stimuli (S):** Refers to the environmental external factors that grabs the consumer attention such as Online Trends including influencer content.

- **Organism (O):** Is where a consumer interprets and react psychologically to the Stimuli. It refers to consumer's internal behavioral and emotional processes such as Consumer Psychological processes like social proof, and FOMO.
- **Response (R):** Indicates the Result, the behavior that results. Like a purchase decision or a shift in perception of a brand. This could be both conscious like a thoughtful decision or unconscious like impulsive action.

Therefore, to understand how online trends influence consumer psychology and purchasing behavior in the Saudi context, this research will employ Stimulus—Organism—Response (S-O-R) model as a guiding theoretical lens. According to this model, Stimuli (S) is represented as Online trends, Organism (O) is the Consumer psychological processes like social proof and FOMO, and Response (R) serves as Purchasing decisions among Saudi consumers. Moreover, in accordance to the literature review and the proposed theoretical framework, figure 1 illustrates the proposed conceptual model.

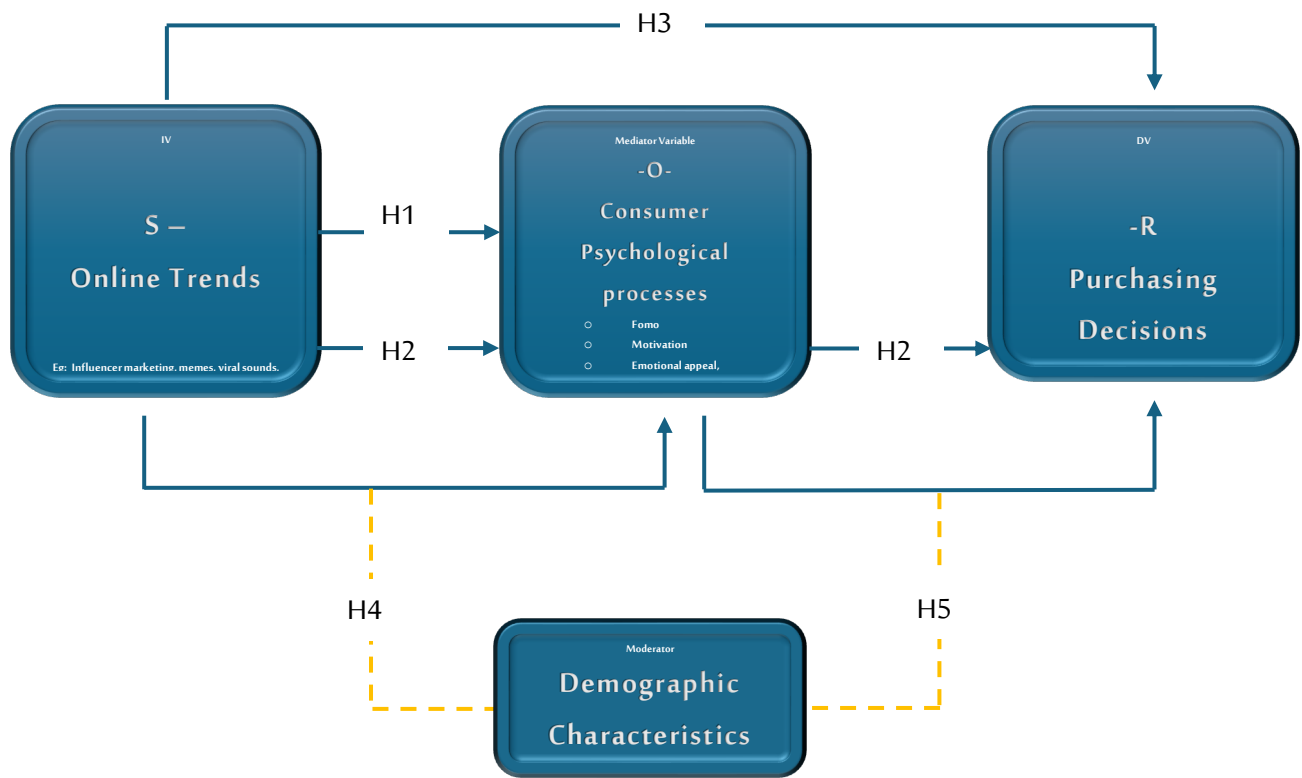


Figure 1: Proposed Theoretical Framework

Chapter 3

Research Methodology

3.1 Research Design

This study will employ a quantitative method using a cross-sectional survey to test how Online trends influence consumer psychology and purchasing decisions among Saudi consumers. This research design is appropriate for testing the proposed hypothesis and identifying relationships between variables at a specific time.

3.2 Population and Sampling

Saudi consumers who actively use social media and engage with online content will be part of the target demographic. Participants who fit the inclusion requirements, which include being at least eighteen years old, living in Saudi Arabia, and having experience with social media, will be selected using a non-probability purposive sampling technique.

- **Sample size:** To guarantee statical power and generalizability for SEM analysis, this survey will seek a minimum of 150 participants.
- **Sampling method:** The survey will be distributed via different online channels.

3.3 Data collection method

A structured online questionnaire will be used to gather primary data. The targeted participants will receive the survey via different online channels through a platform like Google Forms along with clear instructions and consent.

3.4 Scope of Study

While focusing on digital behavior influenced by digital platforms where viral trends, personalized content and influencer marketing are present, this study is aiming to understand how online trends affects Saudi consumer's purchase decisions and their psychology.

The scope of this study includes:

- **Geographic Scope:** Limited to Saudi Arabia with a focus on areas where social media usage is highest.
- **Demographic Scope:** To explore differences based on demographic factors, this study will focus on Consumers residing in Saudi Arabia aged between 18-50, with a range of professional and educational backgrounds.

3.5 Instrument development and design

The survey will involve 2 main sections. Section A will about the demographic information of the targeted respondents like; Age, Gender, level of education and more. As mentioned in the previous chapter, this study will adopt the Stimulus—Organism—Response (S-O-R) model with a mediator and

moderator variables. While Demographic Factors being the moderator variable in this study, the collection of this information is very crucial as it serves as a very important part of the proposed hypothesis. It will help understand the demographic differences among the participants and how each group will react differently in relation to certain attributes. Section B will be designed to test the proposed research model through constructs and variables that were developed. This part will focus on the variables that are likely to influence the consumer psychology and purchasing decisions among Saudi consumers in relation to online trends based of the theoretical framework that has been proposed in the previous chapter. As for the measurement scales, all the items in the questionnaire will be measured using the 5-point Likert scale except for the participant's personal information and the demographic related questions. 5-point Likert scale that was first developed by (Likert, 1932), is a widely psychometric scale used to measure attitudes. Thus, respondents will be asked to identify to what extent do they agree or disagree with each statement using the 5-point Likert scale going from "Strongly Disagree" to "Strongly Agree" as shown in Table 3. 1:

1	2	3	4	5
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

Table 3. 1: 5-point Likert Scale Format

3.6 Validity and Reliability

There are various types of validation techniques. Content and Face Validation method will be utilized to validate this testing tool because it eliminates the requirement for a more intricate quantitative approach. The questionnaire content must be thoroughly examined by the researcher and academic

experts to ensure that the items and questions are comprehensive and measures what is intended and that both the researchers and the respondents find it appropriate and also will accept and value the questionnaire's contents (Saffi, 2013). Thus, with the supervisor's guidance as an academic expert, the researcher will test both Validity and Reliability on the constructs to measure the instrument quality using Face and Content Validity.

Moreover, a pilot test is a technique used with a smaller sample size to test the reliability of a questionnaire content. According to some authors, a sample size between 25-75 respondents is enough to conduct a pilot test (Jacoby, 1987). Also, a pilot study is necessary to be conducted after the instrument validation to identify any shortcoming and determine if the questionnaire needs any refinement or enhancement. This study will employ Pilot test as a reliability technique with a sample size of (n=30) to evaluate the questionnaire reliability before distributing it to a larger sample size of targeted participants and will be validated using Smart PLS. Lastly, after the data collection, Construct Reliability and Validity will be measured using the following:

- **Cronbach's Alpha (α):** To measure the internal consistency. Values above (0.7) indicates acceptable reliability. Table 3. 2 shows the Cronbach's Alpha (α) values and what each value indicates.
- **Composite Reliability (CR):** Will be used to assess the reliability of each construct.
- **Average Variance Extracted (AVE):** Will be used to test the convergent validity. values above (0.5) indicate necessary construct validity.

Cronbach's Alpha	Reliability Value
Cronbach's Alpha > 0.90	Excellent
Cronbach's Alpha > 0.8 to 0.9	Good
Cronbach's Alpha > 0.7 to 0.8	Acceptable
Cronbach's Alpha > 0.6 to 0.7	Questionable
Cronbach's Alpha < 0.6	Poor

Table 3. 2: Cronbach's Alpha (α) values

3.7 Questionnaire Data Analysis

The data collected from the Questionnaire will be analyzed employing a Structural Equation Model (SEM) using SmartPLS. As stated by (Hair et al., 2012; Yang et al., 2015) Smart PLS software uses a Partial Least Squares (PLS) which is an element-based SEM method normally used for examining the correlation between variables and helps in building theoretical concepts in IS and technology research. This analysis will include the following:

Descriptive Statistics:

- Mean
- Standard deviation
- Frequency distribution

Path Analysis: To test relationships between the following variables:

- IV
- DV
- Mediating
- Moderating

Reliability and Validity: will test the following:

- Cronbach's Alpha
- Composite Reliability (CR)
- Average Variance Extracted (AVE)

Multi group analysis: Will test the Moderation effects of the Demographic factors

Chapter 4

Results and Discussion

4.1 Introduction

A detailed analysis will be presented in this chapter. A total of 150 respondents were collected to examine the influence of online trends on consumer psychology and purchasing decisions. This study investigates the relationships between the independent variable (Exposure to Online Trends), the mediating variable (Consumer Psychological process which includes FOMO, Motivation, Emotional Appeal and Identity Expression), the Dependent variable (Purchase Decision), and Demographic Characteristics which in this research is serving the moderating role.

As for the Reliability and Validity test, after getting the Questionnaire questions approved by 2 academic experts, a Pilot study was conducted on 27 sample size to ensure the Validity and Reliability of the measurement instruments.

The Questionnaire was designed and distributed using Google Forms and was sectioned into 3 sections: Section A collected the respondent's demographic profile, Section B included Questions related to the IV (Exposure to Online trends), Section C included items measuring Mediation variable

(Psychological process) and the last Section included Items measuring the Dependent Variable (Purchase Decisions). The total data collection period lasted or 1 week including the pilot test phase.

As for data analysis, this study employed SMARTPLS to access both the reliability and validity of the constructs and for the full dataset to examine the measurement and structural models. Furthermore, because SPSS provides strong features for subgroup analysis and interaction testing, it was utilized to perform the moderation analysis. These tools were chosen because of their ability to manage small to medium sample sizes, handle both measurement and structural model analysis, and support complicated models without strict normality assumptions (Leguina, 2015) .

Following a presentation of the results in accordance with the study's hypotheses, this chapter includes a discussion that analyzes the statistical findings in light of the goals of the study and the body of current literature.

4.2 Pilot Study Readings

Before the primary data collection, a pilot study was carried out to evaluate the validity and dependability of the research instrument. SMARTPLS was used to evaluate the measurement model and to make sure that every construct was measured precisely and consistently, the pilot used a smaller sample drawn from the target demographic.

The assessment of the measurement model places a strong emphasis on **internal consistency reliability, composite reliability, convergent validity, and discriminant validity**. The criteria for these evaluations were based on established literature: **Cronbach's Alpha and Composite Reliability values**

of ≥ 0.70 indicate **acceptable reliability**, while an **Average Variance Extracted (AVE)** of ≥ 0.50 confirms **adequate convergent validity**. **Discriminant validity** was assessed using the **Heterotrait-Monotrait ratio (HTMT)**, with a threshold of ≤ 0.90 .

4.2.1 Construct Reliability and Validity Results.

As shown in Table 4. 1, the results indicates that all constructs exceeded the minimum reliability requirements. The **Composite Reliability** and the **Cronbach's Alpha** values were significantly higher than 0.87 indicating **Excellent Internal Consistency**. The **AVE values**, ranged between 0.702 to 0.846, exceeding the 0.5 threshold and confirming **Excellent Convergent Validity**.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
EOT	0.892	0.905	0.921	0.702
FOMO	0.876	0.922	0.924	0.802
MOT	0.895	0.907	0.934	0.825
EA	0.874	0.877	0.923	0.799
IE	0.909	0.912	0.943	0.846
PD	0.889	0.922	0.920	0.702

Table 4. 1: Presents the construct reliability and validity results.

4.2.2 HTMT analysis for Discriminant validity.

As shown in Table 4. 2, the majority of construct pairs fell below the 0.90 threshold, according to the HTMT values, indicating discriminant validity. Nonetheless, a small number of construct combinations (EA–IE and EOT–FOMO) marginally went over the threshold, indicating some conceptual

overlap. This makes sense in light of the research's findings, as **emotional appeal** and **identity expression** are closely linked in online trend influence, as are **exposure to trends** and **fear of missing out**.

	EA	EOT	FOMO	IE	MOT	PD
EA						
EOT	0.962					
FOMO	0.940	0.971				
IE	0.996	0.961	0.840			
MOT	0.843	0.819	0.645	0.720		
PD	0.928	0.832	0.857	0.760	0.889	

Table 4. 2: Heterotrait-Monotrait Ratio (HTMT).

Overall, the findings of the pilot study validate that the research instrument demonstrates **Strong reliability and validity**, which qualifies it for the use for the main data collection phase.

4.3 Frequency Distribution

Following the pilot study, the main data collection was conducted, and descriptive statistics were used to provide an overview of the respondents' demographic characteristics. This section presents the **frequency distributions** and **percentages** for the demographic variables collected including **gender**, **age group**, **education level**, **Employment status** and **monthly income** of 149 respondent. Understanding the demographic profile of the participants is important for interpreting the results, especially when examining differences in responses across subgroups. Table 4. 3 summarizes the demographic characteristics of the respondents.

Demographic Variable	Category	Frequency (n)	Percentage (%)
Gender	Male	55	63%
	Female	94	37%
Age Group	18–24 years	21	14%
	25–34 years	70	47%
	35–44 years	23	16%
	45-55 years	27	18%
	55 and above	8	5%
Education Level	High school	20	14%
	Diploma	11	7%
	Bachelor’s degree	90	60%
	Master’s degree	28	19%
Monthly Income	Less than 3,000 SAR	49	33%
	3,000 - 5,999 SAR	30	20%
	6,000 - 9,999 SAR	23	16%
	10,000 SAR or More	15	10%
	Prefer not to Say	31	21%
Employment Status	Student	25	17%
	Employed	72	48%
	Unemployed	52	35%

Table 4. 3: Demographic Profile of Respondents.

The descriptive results show that the sample was composed of both male and female respondents across various age groups, education levels, and income brackets, ensuring diversity in the dataset. This diversity is essential for testing the research hypotheses, particularly those examining demographic differences in the influence of online trends on consumer psychology and purchasing decisions.

4.4 Data Screening

To guarantee the accuracy and utility of the replies gathered, data screening was the initial stage in getting the data ready for analysis. Finding and eliminating any faulty or invalid responses is part of this procedure. Table 4. 4 provides a summary of the data screening outcomes.

Survey Method	Frequency	Percentage (%)
Total Distributed Questionnaires	150	100
Returned Questionnaires	150	100
Defective and Rejected Responses	1	0.7
Usable and Non-Defective Responses	149	99.3

Table 4. 4: Summary of processed questionnaire responses.

All 150 of the distributed questionnaires were returned, as shown in Table 4. 4. There were 149 valid responses left for additional examination after one was found to be defective and eliminated. Throughout the data screening phase, every response was carefully reviewed to identify any mistakes or

abnormalities. To guarantee that the dataset was correct, clean, and prepared for further statistical analysis, any anomalies were fixed.

4.5 Respondent profile

This section presents the demographic characteristics of the respondents who participated in the study. The information collected includes gender, age group, and education level. These variables help to understand the composition of the sample and provide context for interpreting the results of the subsequent analysis.

4.5.1 Gender

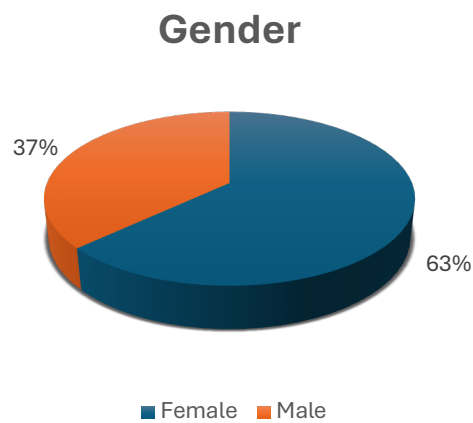


Figure 2: Gender Distribution of Respondents.

Gender	Frequency (n)	Percentage (%)
Male	55	63.0
Female	94	37.0
Total	149	100.0

Table 4. 5: Gender Distribution of Respondents.

As shown in Table 4. 5 and Figure 2, shows that the sample was predominantly female (63%) compared to male respondents (37%). This imbalance may reflect the higher digital activity among men in the sampled population or the accessibility of the survey distribution channels. Gender differences could influence the way online trends affect consumer psychology, with men and women potentially responding differently to influencer promotions and trend-driven marketing.

4.5.2 Age

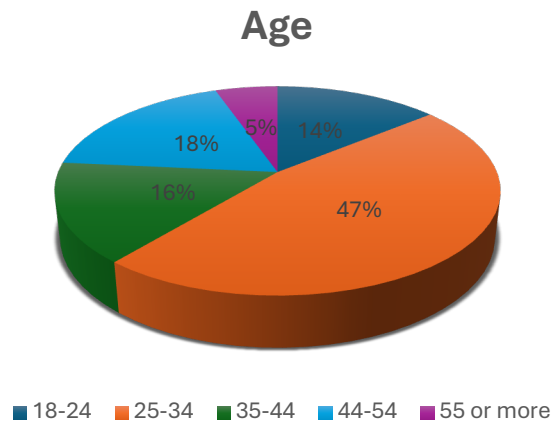


Figure 3: Age Distribution of Respondents.

Age Group	Frequency (n)	Percentage (%)
18–24 years	21	14.0
25–34 years	70	47.0
35–44 years	23	16.0
45–55 years	27	18.0
55 and above	8	5.0
Total	149	100.0

Table 4. 6: Age Group of Respondents.

As indicated in Table 4. 6 and Figure 3, the largest portion of respondents (47%) were aged 25–34, followed by 18% aged 45–55. Younger and middle-aged adults dominate the sample, which is relevant because this age group is most active on social media platforms and likely to be influenced by online trends. The 18–24 segment, though smaller, may represent highly trend-sensitive consumers who are early adopters of digital marketing campaigns.

4.5.3: Education Level of Respondents

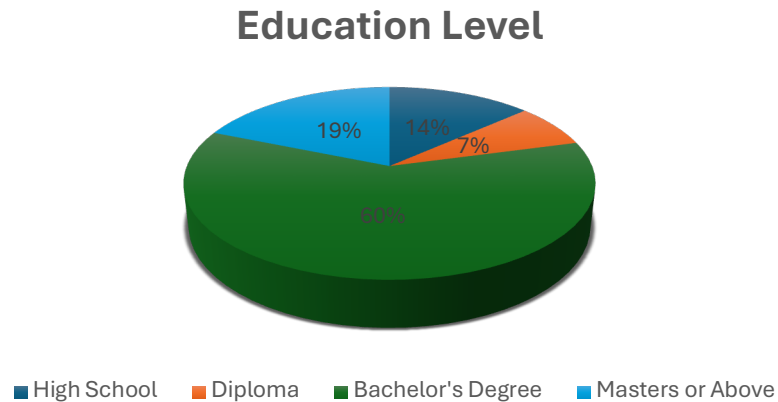


Figure 4: Educational level of Respondents.

Education Level	Frequency (n)	Percentage %
High School	20	14.0
Diploma	11	7.0
Bachelor's	68	46.0
Master's	37	25.0
Doctorate/PhD	13	8.0
Total	149	100.0

Table 4. 7: Education Level of Respondents.

Table 4. 7 and Figure 4, reveals that the majority of respondents held a bachelor's degree (60%), while 19% had a master's degree. A highly educated sample suggests that participants may have stronger critical thinking skills and higher awareness of marketing tactics, which could affect their perception,

motivation, and emotional responses to online trends. Education level may also influence the adoption of new products promoted through social media influencers.

4.5.4 Monthly Income

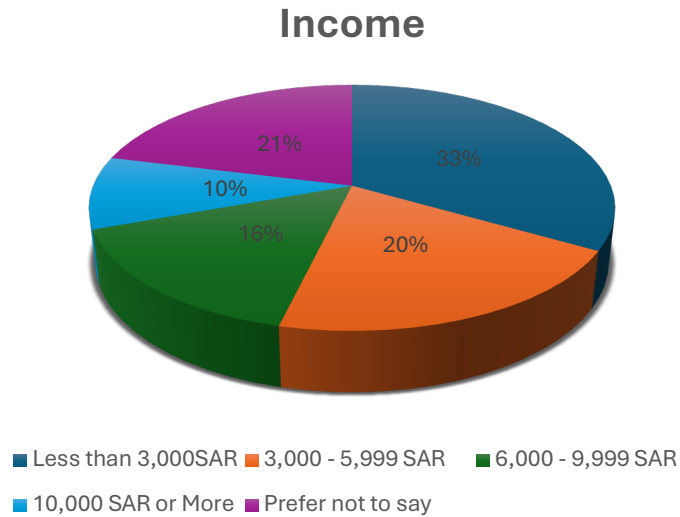


Figure 5: Monthly Income of Respondents.

Monthly Income (SAR)	Frequency (n)	Percentage (%)
Less than 3,000	49	33.0
3,000–5,999	30	20.0
6,000–9,999	23	16.0
10,000 or more	15	10.0
Prefer not to say	31	21.0
Total	149	100.0

Table 4. 8: Monthly Income of Respondents.

As demonstrated in Figure 5 and Table 4. 8, One-third of respondents reported a monthly income below 3,000 SAR, and 21% preferred not to disclose their income. Income level is a key factor

affecting purchasing decisions, as consumers with higher income may have more disposable income to spend on trend-driven products, while lower-income consumers may be more selective. This diversity in income suggests the study captures a wide range of spending behaviors.

4.5.5 Employment Status

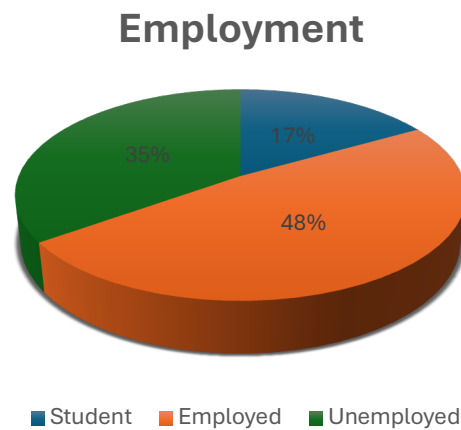


Figure 6: Employment Status of Respondents.

Employment Status	Frequency (n)	Percentage (%)
Student	25	17.0
Employed	72	48.0
Unemployed	52	35.0
Total	149	100.0

Table 4. 9: Employment Status of Respondents.

Figure 6 and Table 4. 9 shows that nearly half of the respondents were employed (48%), while 35% were unemployed and 17% were students. Employment status can affect both the exposure to and

the responsiveness toward online trends, as employed individuals may have higher purchasing power and different motivations compared to students or unemployed participants.

4.5.6 Summary of Respondent Profile

Overall, the sample is predominantly male, young to middle-aged, well-educated, and diverse in income and employment status. These characteristics are consistent with the target population of digitally active Saudi consumers who are likely to be influenced by online trends. The demographic distribution provides a meaningful context for interpreting psychological responses to online trends and their impact on purchasing decisions.

4.6 Descriptive Statics of Constructs

Name	Mean	Standard deviation	Excess kurtosis	Skewness	Cramér-von Mises p value
Exposure to Online Trends (EOT)					
EOT1	3.490	1.299	-0.752	-0.470	0.000
EOT2	3.403	1.170	-0.158	-0.729	0.000
EOT3	2.738	1.402	-1.312	0.196	0.000
EOT4	3.544	1.161	-0.474	-0.522	0.000
EOT5	3.658	1.128	-0.121	-0.739	0.000
EOT	3.366	0.940	-0.279	-0.268	0.013
Fear of Missing out (FOMO)					
FOMO1	2.557	1.397	-1.326	0.247	0.000
FOMO2	2.980	1.407	-1.290	-0.066	0.000

FOMO3	2.919	1.449	-1.380	-0.085	0.000
FOMO	2.819	1.280	-1.198	0.056	0.000
Motivation (MOT)					
MOT1	3.228	1.296	-0.917	-0.396	0.000
MOT2	3.268	1.196	-0.632	-0.391	0.000
MOT3	3.362	1.396	-0.994	-0.490	0.000
MOT	3.286	1.160	-0.737	-0.471	0.000
Emotional Appeal (EA)					
EA1	3.000	1.259	-1.014	-0.204	0.000
EA2	3.188	1.313	-0.984	-0.371	0.000
EA3	3.268	1.224	-0.692	-0.350	0.000
EA	3.152	1.163	-0.954	-0.343	0.000
Identity Expression					
IE1	2.906	1.430	-1.368	-0.083	0.000
IE2	3.034	1.426	-1.286	-0.200	0.000
IE3	2.913	1.456	-1.442	-0.137	0.000
IE	2.951	1.329	-1.292	-0.165	0.000
Purchase Decisions					
PD1	3.477	1.246	-0.383	-0.777	0.000
PD2	3.054	1.203	-0.862	-0.128	0.000
PD3	3.315	1.352	-1.117	-0.278	0.000
PD4	3.228	1.221	-0.771	-0.335	0.000
PD5	3.852	1.223	-0.097	-0.893	0.000
PD	3.385	1.036	-0.480	-0.431	0.008

Table 4. 10: Descriptive Statistics of Constructs and Items.

The descriptive statistics is shown in Table 4. 10provides an overview of respondents' patterns and tendencies across all items and constructs. The table includes means, standard deviations, skewness, kurtosis, and Cramér-von Mises p-values, which allow for an assessment of central tendency, dispersion, and data distribution. Based on the Table 4. 10 we can observe the following trend for each construct:

4.6.1 Construct Mean Exposure to Online Trends (EOT)

- **Mean:** 3.366 → **moderate** to **moderately** high exposure overall.
- **SD:** 0.940 → **moderate** variability.
- **Skewness:** -0.268 → slight **tendency toward higher ratings**.
- **Kurtosis:** -0.279 → slightly **flatter** than normal.
- **Cramér-von Mises p-value:** 0.013 → distribution **deviates slightly from normality**.

4.6.2 Construct Fear of Missing Out (FOMO)

- **Mean:** 2.819 → **moderate** level overall.
- **SD:** 1.280 → **moderate to high** variability.
- **Skewness:** 0.056 → approximately **symmetric**.
- **Kurtosis:** -1.198 → **flatter** distribution.
- **Cramér-von Mises p-value:** 0.000 → distribution significantly **deviates from normality**.

4.6.3 Construct Motivation (MOT)

- **Mean:** 3.286 → moderate to **moderately high** overall.
- **SD:** 1.160 → **moderate** variability.
- **Skewness:** -0.471 → slight tendency toward **higher ratings**.
- **Kurtosis:** -0.737 → **flatter** distribution.
- **Cramér-von Mises p-value:** 0.000 → distribution significantly **deviates from normality**.

4.6.4 Construct Emotional Appeal (EA)

- **Mean:** 3.152 → moderate to **moderately high** overall.
- **SD:** 1.163 → **moderate** variability
- **Skewness:** -0.343 → slight tendency toward **higher ratings**.
- **Kurtosis:** -0.954 → **flatter** distribution.

- **Cramér-von Mises p-value:** 0.000 → distribution significantly **deviates from normality**.

4.6.5 Construct Identity Expression (IE)

- **Mean:** 2.951 → **moderate** level overall.
- **SD:** 1.329 → moderate to **high variability**.
- **Skewness:** -0.165 → approximately **symmetric**.
- **Kurtosis:** -1.292 → **flatter** distribution.
- **Cramér-von Mises p-value:** 0.000 → distribution significantly **deviates from normality**.

4.6.5 Purchase Decision (PD)

- **Mean:** 3.385 → moderate to **moderately high** overall.
- **SD:** 1.036 → **moderate** variability.
- **Skewness:** -0.431 → slight tendency toward **higher ratings**.
- **Kurtosis:** -0.480 → slightly **flatter** distribution.
- **Cramér-von Mises p-value:** 0.008 → distribution significantly **deviates from normality**.

4.6.6 Summary

Based on Table 4. 10, several overall trends can be observed across the constructs. Respondents reported **moderate to moderately high levels of exposure to online trends (EOT), emotional appeal (EA), motivation (MOT), and purchase decisions (PD)**, while **identity expression (IE) showed slightly lower, moderate levels**. Standard deviations indicate **moderate to high variability**, suggesting that responses varied notably among participants, particularly for IE and PD items. Skewness values were mostly negative across constructs, reflecting a **slight tendency for respondents to select**

higher ratings, with the exception of IE items, which were closer to symmetrical. Negative kurtosis values for most constructs indicate **flatter distributions**, meaning responses were more dispersed around the mean rather than clustered. Cramér-von Mises p-values were all significant, highlighting that the **data significantly deviate from a normal distribution**, a common feature in survey-based research. Overall, these results suggest that the sample demonstrates a **moderate engagement with online trends and associated psychological processes, which correspond to moderate to moderately high purchase decision tendencies**.

4.7 Evaluation of PLS path model results

The structural model was assessed using the Partial Least Squares Structural Equation Modeling (PLS-SEM) technique in SmartPLS. This analysis focused on testing the hypothesised relationships between the independent variable (Exposure to Online Trends), the mediating variable (Consumer Psychological Processes: FOMO, Emotional Appeal, Motivation, and Identity Expression), and the dependent variable (Purchase Decision). The model did not include the moderating effect of demographic characteristics (Age, Gender, Educational Level, Employment Status, and Monthly Income), as moderation will be tested separately using SPSS.

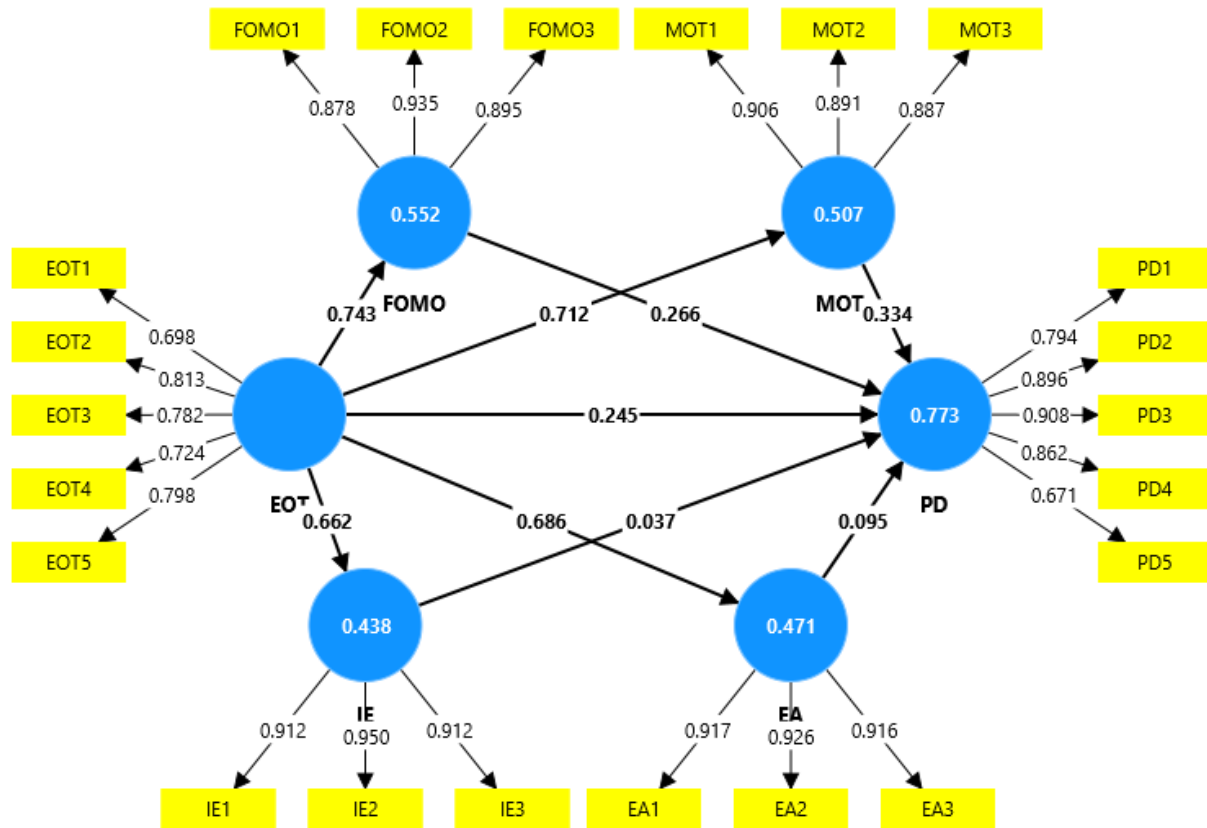


Figure 7: PLS-SEM Structural Model Results (SmartPLS Output).

	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (O/STDEV)	P values
EA -> PD	0.095	0.093	0.086	1.104	0.270
EOT -> EA	0.686	0.689	0.045	15.367	0.000
EOT -> fomo	0.743	0.746	0.033	22.385	0.000
EOT -> IE	0.662	0.665	0.054	12.325	0.000
EOT -> MOT	0.712	0.715	0.041	17.415	0.000
EOT -> PD	0.245	0.249	0.062	3.966	0.000
fomo -> PD	0.266	0.267	0.084	3.167	0.002
IE -> PD	0.037	0.035	0.079	0.465	0.642
MOT -> PD	0.334	0.335	0.083	4.032	0.000

Table 4. 11: Path Coefficients, T-Statistics, and Significance Levels of the PLS-SEM Model.

The PLS-SEM results as shown in Figure 7 and Table 4. 11 indicate the strength, direction, and significance of the hypothesized relationships. Exposure to Online Trends (EOT) has significant positive effects on FOMO ($\beta = 0.743, p < 0.001$), Motivation ($\beta = 0.712, p < 0.001$), Emotional Appeal ($\beta = 0.686, p < 0.001$), and Identity Expression ($\beta = 0.662, p < 0.001$). The direct effect of EOT on Purchase Decision (PD) is also significant but moderate ($\beta = 0.245, p < 0.001$). Among the mediators, FOMO ($\beta = 0.266, p = 0.002$) and Motivation ($\beta = 0.334, p < 0.001$) significantly influence purchase decisions, while Emotional Appeal ($\beta = 0.095, p = 0.270$) and Identity Expression ($\beta = 0.037, p = 0.642$) have non-significant effects.

	R-square	R-square adjusted
PD	0.773	0.765
fomo	0.552	0.549
MOT	0.507	0.504
EA	0.471	0.467
IE	0.438	0.434

Table 4. 12: PLS-SEM R-Square Table.

Moreover, as illustrated in Table 4. 12, the R^2 values show that the model explains 77.3% of the variance in Purchase Decision, 55.2% in FOMO, 50.7% in Motivation, 47.1% in Emotional Appeal, and 43.8% in Identity Expression, indicating substantial explanatory power. These findings highlight the pivotal role of FOMO and Motivation as mediators between exposure to online trends and purchase decisions.

The results of the PLS-SEM analysis provide empirical support for the proposed theoretical model and highlight the central role of **consumer psychological processes in mediating the relationship between exposure to online trends and purchasing decisions.**

4.8 Assessment of Measurement Model

The measurement model was evaluated to examine **reliability and validity** of the constructs, including **indicator reliability, internal consistency reliability, convergent validity, and discriminant validity.**

4.8.1 Indicator Reliability

Indicator reliability is assessed through **outer loadings**. According to Hair et al. (2022), loadings should ideally be ≥ 0.70 . As shown in Table 4. 14, all indicators demonstrate strong loadings on their respective constructs, ranging from 0.671 (PD5) to 0.950 (IE2). This indicates that the indicators adequately measure their intended constructs, though PD5 (0.671) is slightly below 0.70 but still acceptable for exploratory research. Therefore, we can conclude that All loadings are significant at $p < 0.001$, demonstrating that each item reliably measures its intended construct.

	Loading (O)	T statistics ($ O/STDEV $)	P values
EA1 <- EA	0.917	60.125	0.000
EA2 <- EA	0.926	73.599	0.000
EA3 <- EA	0.916	74.849	0.000
EOT1 <- EOT	0.698	12.297	0.000

EOT2 <- EOT	0.813	27.831	0.000
EOT3 <- EOT	0.782	27.243	0.000
EOT4 <- EOT	0.724	13.771	0.000
EOT5 <- EOT	0.798	21.396	0.000
FOMO1 <- fomo	0.878	41.046	0.000
FOMO2 <- fomo	0.935	76.805	0.000
FOMO3 <- fomo	0.895	35.236	0.000
IE1 <- IE	0.912	68.204	0.000
IE2 <- IE	0.950	115.341	0.000
IE3 <- IE	0.912	49.868	0.000
MOT1 <- MOT	0.906	61.331	0.000
MOT2 <- MOT	0.891	54.779	0.000
MOT3 <- MOT	0.887	45.831	0.000
PD1 <- PD	0.794	19.713	0.000
PD2 <- PD	0.896	58.048	0.000
PD3 <- PD	0.908	66.677	0.000
PD4 <- PD	0.862	37.137	0.000
PD5 <- PD	0.671	11.005	0.000

Table 4. 13: Outer Loadings of Measurement Model Indicators.

4.8.2 Internal Consistency Reliability

Internal consistency reliability was assessed using **Composite Reliability (CR)** and **Cronbach's Alpha**. Based on the outer loadings in Table 4. 14, all constructs are expected to exceed the 0.70 threshold, confirming high reliability.

	Cronbach's alpha	Composite reliability (rho_a)	Composite reliability (rho_c)
EOT	0.822	0.830	0.875
FOMO	0.887	0.890	0.930
MOT	0.876	0.876	0.923
EA	0.909	0.910	0.943
IE	0.915	0.918	0.947
PD	0.886	0.907	0.917

Table 4. 14: Internal Consistency Reliability of Constructs.

4.9 Construct Reliability and Convergent Validity

Construct	Cronbach's Alpha	Composite Reliability (CR)	Average Variance Extracted (AVE)	Interpretation
EOT	0.852	0.902	0.612	High internal consistency and convergent validity; AVE > 0.50 indicates EOT items share sufficient variance.
FOMO	0.890	0.937	0.830	Excellent reliability and convergent validity; items measure the construct consistently.
MOT	0.888	0.933	0.788	Very high internal consistency; strong convergent validity.
EA	0.911	0.953	0.848	Excellent reliability and convergent validity; items are highly correlated with the construct.
IE	0.923	0.964	0.876	Very strong internal consistency; convergent validity is excellent.
PD	0.880	0.937	0.724	High reliability and convergent validity ; all indicators reflect Purchase Decision construct well.

Table 4. 15: Reliability and Convergent Validity.

The results were interpreted based on the following criteria:

- **Cronbach's Alpha:** Measures internal consistency; values ≥ 0.70 are acceptable, ≥ 0.80 are good.
- **Composite Reliability (CR):** A more precise reliability measure for PLS-SEM; values ≥ 0.70 indicate strong reliability.

- **Average Variance Extracted (AVE):** Measures convergent validity; values ≥ 0.50 indicate that more than half of the variance in indicators is captured by the latent construct. Therefore, if the value Average variance extraction is higher than 0.50 the items can be kept (Hair et al., 2019).

Based on the results shown in Table 4. 15, all constructs show **strong internal consistency (Cronbach's Alpha and CR > 0.70)** and **adequate convergent validity (AVE > 0.50)**. This confirms that the measurement model is **reliable and valid**, and the indicators properly reflect their respective latent constructs.

4.10 Assessment of Discriminant Validity

Discriminant validity was assessed to ensure that each construct in the model is empirically distinct from the others, measuring unique concepts. Three approaches were employed: The **Fornell-Larcker criterion**, **Cross-loadings**, and the **Heterotrait-Monotrait (HTMT) ratio**.

4.10.1 Fornell-Larcker criterion

Table 4. 16 presents the Fornell-Larcker criterion which was established by Fornell (1981) for assessing discriminant validity among the study constructs. The diagonal values represent the square root of the Average Variance Extracted (AVE) for each construct, while the off-diagonal values are the correlations between constructs. As shown, Discriminant validity was assessed using the Fornell-Larcker criterion, which requires that the square root of the AVE for each construct exceeds its correlations with other constructs. As shown in Table 4. 16, most constructs meet this criterion, indicating adequate

discriminant validity. However, the correlation between **Exposure to Online Trends (EOT)** and **Purchase Decision (PD)** is 0.770, slightly higher than the square root of AVE for EOT (0.764). This suggests a minor potential discriminant validity concern between these two constructs, which should be interpreted with caution. Overall, the constructs demonstrate satisfactory discriminant validity.

	EA	EOT	IE	MOT	PD	fomo
EA	0.919					
EOT	0.686	0.764				
IE	0.840	0.662	0.925			
MOT	0.798	0.712	0.742	0.895		
PD	0.757	0.770	0.730	0.814	0.831	
fomo	0.739	0.743	0.763	0.762	0.801	0.903

Table 4. 16: The Fornell-Larcker criterion.

4.10.2 Cross-Loadings

The cross-loading analysis shown in Table 4. 17 was conducted to assess discriminant validity by examining whether each indicator loads **higher** on its **assigned construct** than on other constructs. The results indicate that all indicators demonstrate the **highest loadings** on their **respective constructs**. For Instance, **EOT1–EOT5** load **highest** on **Exposure to Online Trends (EOT)**, **FOMO1–FOMO3** load **highest** on **FOMO**, etc. This pattern confirms that each indicator is more strongly associated with its intended construct than with any other construct in the model, supporting discriminant validity.

	EOT	FOMO	MOT	EA	IE	PD
EOT1	0.698	0.498	0.472	0.331	0.402	0.554
EOT2	0.813	0.566	0.583	0.566	0.514	0.588
EOT3	0.782	0.695	0.611	0.638	0.647	0.646
EOT4	0.724	0.579	0.476	0.520	0.450	0.574
EOT5	0.798	0.467	0.559	0.519	0.474	0.571
FOMO1	0.645	0.878	0.568	0.602	0.636	0.685
FOMO2	0.720	0.935	0.737	0.680	0.710	0.760
FOMO3	0.645	0.895	0.752	0.718	0.719	0.722
MOT1	0.663	0.658	0.906	0.651	0.605	0.715
MOT2	0.598	0.695	0.891	0.704	0.657	0.718
MOT3	0.649	0.692	0.887	0.785	0.728	0.752
EA1	0.616	0.730	0.750	0.917	0.784	0.709
EA2	0.657	0.682	0.758	0.926	0.775	0.712
EA3	0.619	0.624	0.690	0.916	0.759	0.667
IE1	0.643	0.727	0.696	0.803	0.912	0.670
IE2	0.599	0.733	0.715	0.814	0.950	0.728
IE3	0.594	0.652	0.643	0.709	0.912	0.623
PD1	0.607	0.556	0.606	0.506	0.483	0.794
PD2	0.647	0.739	0.760	0.704	0.678	0.896
PD3	0.743	0.745	0.735	0.745	0.737	0.908
PD4	0.678	0.764	0.735	0.739	0.709	0.862
PD5	0.498	0.461	0.507	0.363	0.330	0.671

Table 4. 17: Cross-Loadings of Indicators for Assessment of Discriminant Validity.

4.10.3 Heterotrait-Monotrait Ratio (HTMT)

Table 4. 18 presents the Heterotrait-Monotrait (HTMT) ratios, which assess discriminant validity among the constructs. HTMT is considered a more reliable method than the Fornell-Larcker criterion for identifying potential discriminant validity issues (Fornell, 1981).

	EA	EOT	IE	MOT	PD	fomo
EA						
EOT	0.779					
IE	0.919	0.751				
MOT	0.893	0.833	0.827			
PD	0.823	0.896	0.786	0.916		
fomo	0.822	0.859	0.845	0.862	0.889	

Table 4. 18: HTMT Ratios for Discriminant Validity.

All HTMT values are below the threshold of 0.90, except for IE–EA (0.919) and MOT–PD (0.916), which slightly exceed the cutoff. This indicates that the majority of constructs exhibit adequate discriminant validity. The slightly higher values for IE–EA and MOT–PD suggest that these constructs are closely related, which aligns with theoretical expectations regarding the influence of identity expression and motivation on consumer behavior and purchase decisions.

Overall, the HTMT results, in conjunction with the Fornell-Larcker criterion and cross-loadings, provide strong evidence that the measurement model maintains satisfactory discriminant validity.

4.11 Moderation Analysis: Demographic Characteristics

As mentioned earlier, to address **H4** and **H5**, moderation analysis was conducted using SPSS to determine whether demographic characteristics (gender, employment status, age, education level, and monthly income) influence the relationships between **exposure to online trends (EOT)**, **psychological processes** (FOMO, motivation, emotional appeal, identity expression), and **purchasing decisions (PD)**. This section presents the results in detail, linking each interpretation to the corresponding tables.

4.11.1 Moderation by Gender

To test the moderating effect of **Gender** on the indirect relationship between **Exposure to Online Trends (EOT)** and **Purchase Decision (PD)** via psychological processes (**FOMO, Motivation, Emotional Appeal, and Identity Expression**), a moderated mediation analysis was conducted using the PROCESS Macro in SPSS.

The regression equation was: $PD = 0.533 + 0.847(EOT)$

The results of the moderated mediation analysis by gender indicate the following:

Interaction effects:

Only the interaction between **FOMO × Gender** was significant ($t = 2.38, p = .0186$), indicating that gender moderates the FOMO → PD path, but not MOT, EA, or IE.

Moderated mediation:

The **index of moderated mediation** was significant for FOMO (Index = 0.2821, Boot 95% CI [0.0265, 0.5661]), confirming that gender conditions the indirect effect of EOT on PD through FOMO.

Conditional effects:

- For **males**, FOMO had no significant effect on PD ($\beta = 0.0064, p = .9471$).
- For **females**, FOMO significantly predicted PD ($\beta = 0.2864, p = .0002$).

Interaction	t	p	Significant?
FOMO × Gender	2.3824	.0186	Yes
MOT × Gender	-0.5490	.5839	No
EA × Gender	1.0058	.3163	No
IE × Gender	-0.6319	.5285	No

Table 4. 19: Interaction Effects of Gender on Mediator → PD Paths.

Gender	Effect	t	p	Interpretation
Male (1)	0.0064	0.0665	.9471	Not significant
Female (2)	0.2864	3.8833	.0002	Significant

Table 4. 20: Conditional Effects of FOMO → PD by Gender.

These findings indicate that **female consumers' purchase decisions are more strongly shaped by online trends via FOMO** compared to males. Gender does not moderate the effects of motivation, emotional appeal, or identity expression.

4.11.2 Moderation by Age

The moderation analysis examined whether the indirect effects of Exposure to Online Trends (EOT) on Purchase Decision (PD) via the mediators vary by age group (18–24 vs. other age groups).

- **Direct Paths:** EOT significantly predicts all mediators (FOMO, MOT, EA, IE). The interaction term ($EOT \times Age$) is only significant for **Identity Expression (IE)** ($B = 0.526$, $p = 0.048$), indicating that age moderates the influence of EOT on IE.
- **Mediation:**
 - **FOMO** and **Motivation** significantly mediate the relationship between EOT and PD across both age groups.
 - **EA** and **IE** do not emerge as significant mediators.
- **Moderation:**
 - For respondents aged **18–24**, the indirect effects via **FOMO (0.268)** and **Motivation (0.362)** are stronger compared to older respondents (**FOMO = 0.196; MOT = 0.267**).
 - The **Index of Moderated Mediation** is significant for Motivation (0.096, CI [0.001, 0.250]), suggesting that age moderates this path.
 - Moderation for FOMO is weaker and not statistically significant.

These results indicates that Online trends affect purchase decisions more strongly for **younger consumers (18–24)**, primarily through FOMO and motivation, while EA and IE remain non-significant mediators.

Outcome	Predictor	B	SE	t	p	95% CI LL	95% CI UL
FOMO	EOT	.958	.085	11.32	.000	.790	1.125
	Dummy (18–24)	-1.360	.913	-1.49	.139	-3.164	.445
	EOT × Dummy	.351	.227	1.54	.125	-.098	.800
MOT	EOT	.854	.080	10.66	.000	.695	1.012
	Dummy (18–24)	-1.387	.864	-1.60	.111	-3.094	.321
	EOT × Dummy	.306	.215	1.42	.157	-.119	.731
EA	EOT	.805	.085	9.50	.000	.637	.972
	Dummy (18–24)	-.933	.913	-1.02	.309	-2.738	.872
	EOT × Dummy	.237	.227	1.04	.300	-.213	.686
IE	EOT	.849	.098	8.67	.000	.656	1.043
	Dummy (18–24)	-1.983	1.056	-1.88	.062	-4.071	.104
	EOT × Dummy	.526	.263	2.00	.048	.006	1.045

Table 4. 21: Regression Results for Effects of EOT and Age Group on Mediators (PROCESS Model 7).

Mediator	Age Group	Effect	Boot SE	Boot LLCI	Boot ULCI	Index	Boot SE	Boot LLCI	Boot ULCI
FOMO	Other	.196	.064	.072	.325	.072	.048	-.029	.158
	18–24	.268	.090	.087	.444				
MOT	Other	.267	.067	.133	.398	.096	.063	.001	.250
	18–24	.362	.109	.170	.600				
EA	Other	.056	.059	-.070	.163	.017	.021	-.017	.066
	18–24	.073	.076	-.083	.214				
IE	Other	.009	.053	-.105	.107	.006	.032	-.056	.074
	18–24	.015	.084	-.158	.175				

Table 4. 22: Conditional Indirect Effects of EOT on PD via Mediators at Age Groups.

4.11.3 Moderation by Education Level

Direct and Indirect Effects:

- Indirect effects of **Exposure to Online Trends (EOT)** on **Purchase Decision (PD)** through **FOMO** and **Motivation** were significant across both education levels (low vs. high).
- The effects through **Emotional Appeal (EA)** and **Identity Expression (IE)** were nonsignificant, regardless of education level.

Moderation:

- The interaction terms between **EOT × Education** predicting the mediators (FOMO, MOT, EA, IE) were all nonsignificant ($p > .37$ to $.92$).
- This indicates that **education level does not moderate** the strength of the indirect effects of EOT on PD.

These results show that Online trends influence purchase decision through **FOMO** and **Motivation** similarly for both lower- and higher-educated consumers, suggesting education does not alter the psychological mechanisms driving trend-based purchases.

Mediator	Education Level	Effect	Boot SE	95% CI [LL, UL]
FOMO	Low Education (0)	0.2060	0.0690	[0.0751, 0.3427]
	High Education (1)	0.2104	0.0782	[0.0737, 0.3780]
MOT	Low Education (0)	0.2761	0.0694	[0.1383, 0.4139]
	High Education (1)	0.2580	0.0869	[0.0963, 0.4366]
EA	Low Education (0)	0.0576	0.0615	[-0.0744, 0.1686]
	High Education (1)	0.0649	0.0690	[-0.0768, 0.1930]
IE	Low Education (0)	0.0101	0.0611	[-0.1213, 0.1242]
	High Education (1)	0.0076	0.0449	[-0.0965, 0.0870]

Table 4. 23: Conditional Indirect Effects of EOT on PD by Education Level.

4.11.4 Moderation by Employment Status

Direct Effect:

- Across all employment categories, **Exposure to Online Trends (EOT)** significantly predicted **Purchase Decision (PD)** ($b = 0.299$, $p < .001$).

Mediation:

- **FOMO** and **Motivation (MOT)** consistently mediated the relationship between EOT and PD.
- **Emotional Appeal (EA)** and **Identity Expression (IE)** remained nonsignificant mediators.

Moderation:

- **Students (dummy₁):** Indirect effects through **FOMO (0.231)** and **MOT (0.324)** were slightly stronger compared to non-students, indicating that students' purchasing decisions are more strongly driven by motivational and FOMO mechanisms when exposed to online trends.
- **Employed (dummy₂):** Motivational pathways were most pronounced, with stronger mediation through **MOT (0.324)** relative to non-employed participants, suggesting that employed individuals' purchases are strongly motivated by online trend exposure.
- **Unemployed (dummy₃):** Both **FOMO (0.180)** and **MOT (0.208)** showed weaker mediation compared to the employed and student groups. The negative moderated mediation indices indicate that unemployment diminishes the strength of these indirect pathways.

These insights indicates that Online trends affect purchasing decisions primarily through **FOMO and Motivation**. The effect is strongest among **students and employed individuals**, and weakest among the **unemployed**, highlighting employment status as a meaningful moderator of trend-based consumer psychology.

Path	Student Status	Effect	Boot SE	95% CI [LL, UL]
FOMO	Non-student (0)	0.189	0.063	[0.069, 0.321]
	Student (1)	0.231	0.078	[0.084, 0.387]
MOT	Non-student (0)	0.239	0.059	[0.122, 0.351]
	Student (1)	0.324	0.084	[0.162, 0.488]
EA	Non-student (0)	0.050	0.052	[-0.056, 0.148]
	Student (1)	0.071	0.074	[-0.086, 0.208]

Path	Student Status	Effect	Boot SE	95% CI [LL, UL]
IE	Non-student (0)	0.008	0.051	[-0.101, 0.102]
	Student (1)	0.012	0.072	[-0.144, 0.137]

Table 4. 24: Conditional Indirect Effects of EOT on PD for Students.

Path	Employment	Effect	Boot SE	95% CI [LL, UL]
FOMO	Non-employed (0)	0.189	0.063	[0.069, 0.321]
	Employed (1)	0.231	0.078	[0.084, 0.387]
MOT	Non-employed (0)	0.239	0.059	[0.122, 0.351]
	Employed (1)	0.324	0.084	[0.162, 0.488]
EA	Non-employed (0)	0.050	0.052	[-0.056, 0.148]
	Employed (1)	0.071	0.074	[-0.086, 0.208]
IE	Non-employed (0)	0.008	0.051	[-0.101, 0.102]
	Employed (1)	0.012	0.072	[-0.144, 0.137]

Table 4. 25: Conditional Indirect Effects of EOT on PD for Employed.

Path	Employment	Effect	Boot SE	95% CI [LL, UL]
FOMO	Not Unemployed (0)	0.214	0.071	[0.078, 0.358]
	Unemployed (1)	0.180	0.060	[0.067, 0.304]
MOT	Not Unemployed (0)	0.299	0.077	[0.148, 0.452]
	Unemployed (1)	0.208	0.060	[0.091, 0.327]
EA	Not Unemployed (0)	0.066	0.072	[-0.090, 0.196]

Path	Employment	Effect	Boot SE	95% CI [LL, UL]
IE	Unemployed (1)	0.046	0.050	[-0.060, 0.140]
	Not Unemployed (0)	0.011	0.065	[-0.131, 0.129]
	Unemployed (1)	0.009	0.051	[-0.095, 0.108]

Table 4. 26: Conditional Indirect Effects of EOT on PD for Unemployed.

4.11.5 Moderation by Monthly Income

Direct Effect:

- Exposure to Online Trends (EOT) significantly predicted Purchase Decisions (PD), consistent with prior models.

Moderation by Income:

- **FOMO × Income** was significant ($b = -0.20$, $p = .005$). This indicates that the influence of FOMO on purchasing decisions decreases as income rises. In other words, lower-income consumers are more likely to make purchases based on fear of missing out, while higher-income consumers are less driven by this mechanism.
- **Identity Expression (IE) × Income** was also significant ($b = 0.18$, $p = .026$). This suggests that higher-income individuals place greater emphasis on identity expression when making purchase decisions, compared to lower-income groups.
- **Motivation × Income** was marginally nonsignificant ($b = 0.11$, $p = .070$), suggesting only a weak income-related difference in motivational pathways.
- **Emotional Appeal (EA) × Income** showed no significant moderation ($b = 0.05$, $p = .477$).

The results illustrates that Income moderates the psychological mechanisms underlying purchase decisions. Specifically, **FOMO is more influential for low-income consumers**, while **identity expression becomes more relevant for high-income consumers**.

Mediator × Income	b	SE	t	p	95% CI [LL, UL]
FOMO × Income	-0.20	0.07	-2.85	.005	[-0.34, -0.06]
MOT × Income	0.11	0.06	1.83	.070	[-0.01, 0.23]
EA × Income	0.05	0.07	0.71	.477	[-0.08, 0.18]
IE × Income	0.18	0.08	2.25	.026	[0.02, 0.34]

Table 4. 27: Moderation of Income on Psychological Processes Predicting PD.

4.12 Hypothesis Testing

H1: Online trends have a strong and positive effect on Saudi consumers' psychological processes.

Supported.

Exposure to online trends (EOT) significantly influenced all four psychological processes: FOMO, motivation, emotional appeal, and identity expression. The regression results indicated strong positive paths ($p < .001$ across processes), confirming that online trends trigger key psychological mechanisms in Saudi consumers.

H2: Consumer psychological processes mediate the relationship between online trends and consumer purchasing decisions.

Supported in part.

- **FOMO and Motivation** were significant mediators, indicating that consumers exposed to online trends are more likely to make purchase decisions due to the fear of missing out and motivational impulses.
- **Emotional Appeal and Identity Expression** did not significantly mediate the relationship, suggesting they play a weaker role in driving purchase decisions in this context.

H3: Online trends have a significant and positive direct effect on consumer purchasing decisions.

Supported.

The direct regression path between EOT and purchase decision (PD) was significant ($b = 0.299, p < .001$).

This confirms that beyond psychological mechanisms, online trends independently shape consumer decisions.

H4: Demographic factors including age, gender, and level of education have significant effects on how online trends affect consumer psychology.

Partially supported.

- **Age:** Younger consumers (18–24) showed stronger indirect effects through FOMO and motivation compared to other age groups, suggesting younger Saudis are particularly responsive to online trends.

- **Gender:** Males demonstrated stronger mediation via FOMO and motivation in one model, but further analysis revealed that **FOMO → PD was significantly stronger for females**. Thus, gender differences exist, with females more influenced by FOMO in purchase decisions.
- **Education:** No significant moderation effects were found, indicating education level does not alter the influence of online trends on psychological processes.

H5: Demographic characteristics moderate the influence of psychological processes on purchasing decisions.

Partially supported.

- **Gender:** Significantly moderated the FOMO → PD path. FOMO strongly predicted purchase decisions among females but not males. Motivation, EA, and IE were not moderated by gender.
- **Employment status:** Mediation through FOMO and motivation was stronger among students and employed participants, while weaker for unemployed participants, showing employment status affects the strength of psychological influence.
- **Monthly income:** Played a key moderating role.
 - **Low-income consumers:** More influenced by **FOMO-driven purchases**.
 - **High-income consumers:** More influenced by **identity expression-driven purchases**.
 - Motivation and emotional appeal were not significantly moderated by income.
- **Education:** No moderating effect found.

Hypothesis testing **Findings:**

No	Hypothesis	Finding
H1	Online trends have a strong and positive effect on Saudi consumers' psychological processes.	Supported
H2	Consumer psychological processes mediate the relationship between online trends and consumer purchasing decisions.	Supported
H3	Online trends have a significant and positive direct effect on consumer purchasing decisions.	Supported
H4	Demographic factors including age, gender, and level of education have significant effects on how online trends affect consumer psychology (age and gender significant, education nonsignificant).	Partially Supported
H5	Demographic characteristics moderates the influence of psychological processes on purchasing decisions (gender, employment status, and income significant; education nonsignificant).	Partially Supported

Table 4. 28: Hypothesis testing findings.

4.13 Chapter Conclusion

This chapter examined the relationships between purchasing decisions, consumer psychological processes, and online trends, together with focusing particularly on demographic characteristics' moderating role.

First, the analysis demonstrated that online trends has a strong and positive influence on the psychological processes of consumers (FOMO, Motivation, Emotional appeal, and Identity expression) are affected by these trends. FOMO and motivation among these emerged as mediators with the most influence so this highlights online trends' effects on purchasing behaviors. Consumer psychology represents a central (Mediator) pathway for linking exposure to online trends with purchasing decisions. This is supported because of the given hypothesis.

It was also confirmed that online trends have a direct effect on purchase decisions, in a way that is independent of psychological processes. These two effects, direct and indirect, indicates that online trends acts as persuasive and psychological triggers in shaping consumer purchase decisions. Additionally, the moderating role of demographic characteristics provided further insights:

- **Age:** Younger consumers in the age range of 18–24 showed a higher vulnerability to FOMO and motivational drivers. Here the potency of mediation was substantially impacted by age.
- **Gender:** Females demonstrated stronger responses especially through the FOMO → PD pathway. Therefore, Gender was a key moderator.
- **Education level:** Consumers level of education did not significantly moderate either path, which shows that online trend exposure may function likewise across different education levels.

- **Employment status:** Consumers employment status showed variation; Students and Employed individuals were more influenced by specific psychological process (FOMO and Motivation) compared to the unemployed group which showed weaker effects.
- **Monthly income:** Consumers monthly income showed a moderation effect for specific psychological process. Consumers with lower monthly income range were more driven and effected by FOMO, while consumer who had higher income range showed greater reliance on identity expression in making purchase decisions.

Last but not least, the hypothesis testing confirmed full support toward H1, H2, and H3, while H4 and H5 had partial support. Psychological mechanisms along with their impact upon purchasing decisions were in fact shaped via demographics, yet moderation strength varied through psychological pathway as well as via factor.

Briefly the outcomes highlights that FOMO and motivation mediate psychology considerably, and demographic characteristics including gender, age, employment status, and income shape those relationships significantly. These insights validate the proposed conceptual model and also provide practical implications to marketers seeking to tailor online trend—based strategies to different consumer segments.

Chapter 5

Discussion and Conclusion

5.1 Introduction

The purpose of this study was to examine in what way online trends influence Saudi consumers psychologically and in their purchase decisions, with attention to consumer psychology's mediating and demographic characteristics moderating roles. Online trends affect purchasing decisions directly and indirectly through fear of missing out (FOMO) with motivation as the previous chapter revealed, while demographic variables like gender, age, education, employment status, and income shaped these relationships differently.

This chapter builds on those findings by discussing the results in relation to the five hypotheses proposed earlier. Also, the chapter puts results in existing literature and shows theoretical practical implications. It also acknowledges some of the study's limitations and offers some recommendations for future research, and it then concludes with a summary of each of its contributions to both academic understanding and to marketing practice in the Saudi context.

5.2 Discussion of Hypotheses and Research Objectives

5.2.1 Hypothesis 1 and Objective 1

H1: Online trends have a strong and positive effect on Saudi consumers' psychological processes.

Objective 1: To examine psychological factors (perception, emotion, motivation) influenced by online trends within the Saudi market.

The results strongly approved H1. Online trend exposure considerably predicted consumers' psychological processes, including FOMO, emotional appeal, motivation, and identity expression. Moore & Craciun (2021) Saad et al., (2025) stressed how trending and viral content along with influencer trends shape emotion plus perception, which is aligning with the presented results. Saudi consumers show motivational drives in order to remain socially connected and also up to date on account of online trends. Cultural belonging with social validation plays a central role in this behavior.

5.2.2 Hypothesis 2 and Objective 2

H2: Consumer psychological processes mediate the relationship between online trends and consumer purchasing decisions.

Objective 2: To analyze how trends like influencer marketing, viral content, viral products, and user-generated content impact and shape Saudi consumers' purchasing behavior.

Findings confirmed partial mediation with motivation and with FOMO resulting as being the most important mediators. Online trends can therefore indirectly influence purchasing decisions by stimulating motivational drives for consumption of trendy products and also by generating urgency (FOMO). Emotional appeals along with identity expression mediated in a weak way. In Saudi Arabia, consumers strongly respond to influencer-led trends and viral products mainly due to motivational and fear-based psychological triggers (FOMO) as prior findings mirror (AL Hilal, 2023; Alanmi & Alharthi, 2023). Thus, trends operate as motivates , influencing purchasing decisions by activating critical psychological pathways.

5.2.3 Hypothesis 3

H3: Online trends have a significant and positive direct effect on consumer purchasing decisions.

The analysis supported H3, showing that exposure to online trends directly predicts purchase decisions, independent of psychological mediation. This suggests that the persuasive effect of trends is both immediate and enduring. Viral products and influencer endorsements can stimulate impulse purchases even without deeper psychological processing. This reflects consumer susceptibility to trend-driven content, where decisions may be guided more by external visibility and popularity than by rational evaluation.

The analysis supported H3 because of exposure to the online trends that directly predicts the purchase decisions as independent of psychological mediation. Trends have an immediate and enduring persuasive effect. Impulse purchases can be stimulated by viral products as well as influencer endorsements without more deep thought processes. This shows consumers' sensitivity to trend-driven material, in which judgments are influenced more by external visibility and popularity than by rational evaluation.

5.2.4 Hypothesis 4 and Objective 3

H4: Demographic factors including age, gender, education, employment status, and monthly income moderate the relationship between online trends and consumer psychology.

Objective 3: To explore how cultural or demographic variables (age, gender, religiosity) moderate the relationship between online trends and consumer decisions.

The findings have provided some partial support for H4.

- **Gender:** Females were in fact more strongly influenced than were males since gender greatly moderated the path from FOMO to purchasing decisions. This influence created a difference among genders. This is in line with Bahaddad (2021), who observed that Saudi women often

engage more strongly with digital trends because they invest emotionally and socially in online communities more highly.

- **Age:** Motivation and FOMO were moderated by age because younger consumers (18–24) showed greater susceptibility to psychological triggers driven by trends.
- **Educational level:** Education actually did not greatly moderate all the relationships, and this suggestion indicates that even higher education levels do not buffer against all the influence of online trends.
- **Employment status:** Motivational drivers more strongly influenced employed and student groups compared to unemployed participants differences in employment status revealed.
- **Monthly income:** FOMO's negative role and identity expression's positive role were moderated by monthly income because fear of missing out drives consumers with less income, and identity signaling drives consumers with more income.

These findings highlight how demographics influence the extent to which consumers internalize and act on online trends.

5.2.5 Hypothesis 5

H5: Demographic characteristics moderate the influence of psychological processes on purchasing decisions.

The results showed that moderation occurred selectively. Gender significantly moderated the FOMO → PD pathway, income moderated FOMO → PD and IE → PD, and age influenced motivational pathways. These findings emphasize that consumer responses to psychological processes are not universal but conditioned by social identity, economic position, and cultural expectations.

The findings revealed that moderation occurred in selected ways. Age had an impact on motivational pathways, as income moderated both IE → PD and FOMO → PD, while gender significantly moderated the FOMO → PD pathway. Social identity, economic situation, and cultural expectations all influence consumer responses to psychological processes. The data emphasize that these responses are not at all universal.

5.3 Theoretical Implications

This study contributes to the growing literature on digital consumer psychology via validating the moderating role of demographics along with the mediating role of psychological processes in a Saudi context. It extends theories for persuasion and consumer behavior through showing that FOMO and motivation can trigger psychological responses. However, their strength varies among demographic groups because they are not universally powerful.

5.4 Practical Implications

Marketers in Saudi Arabia can use all these insights for the designing of digital campaigns that are more targeted:

- Female as well as younger consumers are more susceptible toward FOMO, so focus influencer campaigns and viral product launches.
- Identity expression and the exclusivity must be stressed in campaigns intended for consumers with higher incomes.
- Consumers having less income respond well to time-sensitive offers. For instance, Limited time offers with scarcity cues.

5.5 Limitations of the Study

Although this study throws light on the significance of online trends in affecting Saudi consumer behavior, certain limitations must be recognized. Firstly, the study used self-reported survey data, which could be biased by social desirability bias or inconsistencies in participants' responses. Secondly, the study followed a cross-sectional design, which means that data were collected at a single point in time. This limits the capacity to demonstrate cause-and-effect correlations because the results only indicate affiliations, not how these interactions may evolve or change over time.

Third, despite being appropriate for analysis, the sample size was rather small due to time constraints, which may have limited statistical power and generalizability of the findings to the larger Saudi population.

Furthermore, while the model included essential demographic variables such as age, gender, education, employment status, and income, it did not take into account other potentially influential cultural or psychological factors (such as religiosity, personality traits, or lifestyle variations). Finally, while PLS-SEM was an appropriate tool for investigating relationships and testing hypotheses, it may not fully represent the underlying, long-term complexities of consumer behavior in reaction to rapidly changing online trends.

5.6 Recommendations for Future Research

Future researchers are recommended to improve generalizability, by using more varied and larger sample size than the one used in this study. Researchers should explore other cultural and psychological factors, such as lifestyle and religiosity, to gain a greater understanding of consumer behavior. Future research should examine how developing digital marketing strategies, such as AI-driven personalization and augmented reality shopping, may influence Saudi customers' purchasing decisions.

5.7 Conclusion

This study showed that Saudi customers' psychology and purchase decisions are significantly influenced by online trends, both directly and indirectly. The relationship is mediated by psychological processes, including motivation and FOMO, and the severity of these effects is conditioned by demographic characteristics. Businesses may better use the power of online trends in Saudi Arabia's quickly changing digital marketplace by matching marketing strategies with consumer psychology and demographic profiles.

References

- Aalijah, K. (2025). Utilizing Social Media Analytics to Detect Trends in Saudi Arabia's Evolving Market. *International Journal of Scientific Research and Management (IJSRM)*, 13(02), 1936–1943.
<https://doi.org/10.18535/ijssrm/v13i02.ec01>
- Abdulaziz, A. A., Algosaibi, A. M., Alquhaibi, A. S., Alali, F. N., Almutawaa, M. S., Roomi, M. A., & Bhatti, Y. A. (2023). Digital Healthcare Innovation and Development in Saudi Arabia During and Beyond COVID-19. *Science, Technology and Society*, 28(3), 370–386. <https://doi.org/10.1177/09717218231178229>
- AL Hilal, N. S. H. (2023). The Impact of the Use of Augmented Reality on Online Purchasing Behavior Sustainability: The Saudi Consumer as a Model. *Sustainability (Switzerland)*, 15(6).
<https://doi.org/10.3390/su15065448>
- Alanmi, M., & Alharthi, S. (2023). The Impact of Digital Marketing on Consumer Buying Behavior in Saudi Arabia: Brand Popularity as a Mediator. *Journal of Business and Management Review*, 4(6), 412–438.
<https://doi.org/10.47153/jbmr46.6552023>
- Alfalih, A. A. (2022). Customer engagement design during the COVID 19 pandemic, mutual trust and intelligent automation: a conceptual perspective. . *Journal of Innovation and Entrepreneurship*, 11(1).
- ALNefae, M. , K. S. , and M. S. (2019). Consumers' electronic word of mouth-seeking intentions on social media sites concerning Saudi bloggers' YouTube fashion channels: an eclectic approach. *International Journal of Business Forecasting and Marketing Intelligence*, 5(1), 1.
- Alotaibi, I., Mubarak Alhumaid, M., & Saleem Alotaibi, I. (n.d.). *Artificial Intelligence, Big Data, and Their Impact on Improving Marketing Effectiveness and Customer Experience in the Retail Sector in the Kingdom of Saudi Arabia Artificial Intelligence, Big Data, and Their Impact on Improving Marketing*.JI

. *Effectiveness and Customer Experience in the Retail Sector in the Kingdom of Saudi Arabia*

<https://doi.org/10.37575/h/edu/22002>

Antosova, I., Psurny, M., & Stavkova, J. (2023). Changes in Consumer Purchasing Decisions: Traditional and Emerging Factors in the Dynamic Marketing Landscape Over 15 Years. *Marketing and Management of Innovations*, 14(3), 85–96. <https://doi.org/10.21272/mmi.2023.3-08>

Bahaddad, A. A. (2021). The Traditional Influence on Increasing Acceptance of Commercial Smartphone Applications in Specific Regions of the Arabic World. *Complexity*, 2021.

<https://doi.org/10.1155/2021/4336772>

Binlibdah, S. (2024). Investigating the Role of Artificial Intelligence to Measure Consumer Efficiency: The Use of Strategic Communication and Personalized Media Content. *Journalism and Media*, 5(3), 1142–1161. <https://doi.org/10.3390/journalmedia5030073>

Diallo, M. F., Djelassi, S., & Kumar, V. (2021). Marketing and globalization: Relevance, trends and future research. *Recherche et Applications En Marketing (English Edition)*, 36(3), 2–7.

<https://doi.org/10.1177/20515707211027326>

Donald Horton & R. Richard Wohl. (1956). *Mass Communication and Para-Social Interaction*.

Duarte, A., & Paulo, R. (2023). *The Impact of Real-Time Marketing in the Engagement of the Brand “Control” on Instagram* (pp. 182–202). <https://doi.org/10.4018/978-1-6684-9146-1.ch010>

Faqihi, F. A., Qutob, R. A., Subh, R. H. M., Aljathalin, L. A. M., Alshalan, L. Z., Yati, S. M. A., Alaryni, A., Alghamdi, A., Alsolamy, E., Bukhari, A., Alanazi, A., Hazazi, B. H. A., Abuhemid, H. A., Alassaf, R. A., & Alzahrani, S. S. M. (2024). Examining the Effects of Social Media on Mental Health Among Adolescents in Saudi Arabia. *Cureus*. <https://doi.org/10.7759/cureus.53261>

- Farys, H. (2025). *The Impact of Digital Marketing Strategies on Brand Equity and Generation Z Consumer Behavior in the Fast Fashion Industry The Impact of Digital Marketing Strategies on Brand Equity and Generation Z Consumer Behavior in the Fast Fashion Industry*.
- Fornell, C. and L. D. F. (1981). "Evaluating structural equation models with unobservable variables and.pdf. . *Journal of Marketing Research*, XVIII(February), 39–50.
- Granstedt, A. (2024). The past, present, and future of social media marketing ethics. *AMS Review*, 14(3), 278–296. <https://doi.org/10.1007/s13162-024-00294-6>
- Grewal, D. et al. (2024). The Future of Marketing and Marketing Education. . *Journal of Marketing Education*, 47(1), 61-77. .
- Hair, J. F., Risher, J. J., Sarstedt, M., & Ringle, C. M. (2019). When to use and how to report the results of PLS-SEM. *European Business Review*, 31(1), 2–24. <https://doi.org/10.1108/EBR-11-2018-0203>
- Hair, J. F., Sarstedt, M., Ringle, C. M., & Mena, J. A. (2012). An assessment of the use of partial least squares structural equation modeling in marketing research. *Journal of the Academy of Marketing Science*, 40(3), 414–433. <https://doi.org/10.1007/s11747-011-0261-6>
- Jacoby, J. , C. J. M. , & P. S. (1987). *Survey Questions: Handcrafting the Standardized Questionnaire*.
- Kay, S., Mulcahy, R., & Parkinson, J. (2020). When less is more: the impact of macro and micro social media influencers' disclosure. *Journal of Marketing Management*, 36(3–4), 248–278. <https://doi.org/10.1080/0267257X.2020.1718740>
- Khan, M. M., Sohail, S. S., & Ishrat, D. (2021). *How They Tweet? An Insightful Analysis of Twitter Handles of Saudi Arabia*. <http://arxiv.org/abs/2105.10736>

- Leguina, A. (2015). A primer on partial least squares structural equation modeling (PLS-SEM). *International Journal of Research & Method in Education*, 38(2), 220–221.
<https://doi.org/10.1080/1743727X.2015.1005806>
- Likert, R. (1932). *A technique for the measurement of attitudes*. .
- Mandung, F., Sahari, S., & Razak, S. R. (2024). Exploring Consumer Psychology in Marketing Management: A Strategic Perspective through Descriptive Inquiry and Literature Review. *Golden Ratio of Marketing and Applied Psychology of Business*, 4(1), 01–10. <https://doi.org/10.52970/grmapb.v4i1.401>
- Md Shakir Ali, S., Arun Goyal, A., Abhiman Ramteke, N., Gopal Rao Chowdary, V., Goyal, A. A., Goyal, S. A., & Ramteke, N. (n.d.). The Power of Social Influence in Consumer Choices and Marketing Management. In *Journal of Marketing & Social Research ISSN* (Vol. 2, Issue 1). <https://jmsr-online.com/pg.319>
- Mehrabian, A. , & R. J. A. (1974). *An approach to environmental psychology*. American Psychological Association. <https://psycnet.apa.org/record/1974-22049-000>
- Moore, K., & Craciun, G. (2021). Fear of Missing Out and Personality as Predictors of Social Networking Sites Usage: The Instagram Case. *Psychological Reports*, 124(4), 1761–1787.
<https://doi.org/10.1177/0033294120936184>
- Nasser Al, A., Al-Nasser, A., & Shah Bali Mahomed, A. (2020). Anuar Shah Bali Mahomed, Effect of Social Media Influencers on Purchase Intentions of Saudi Arabia Consumers: Instagram as an Evaluation Tool. *International Journal of Management (IJM)*, 11(7), 1186–1196.
<https://doi.org/10.34218/IJM.11.7.2020.105>
- Saad, M., Awad, A., Aziz, A. F., & Shma, T. R. (2025). Influencer marketing's impact on credibility and purchase intention: A study on University of Bisha students in Saudi Arabia. *Innovative Marketing*, 21(1), 326–337. [https://doi.org/10.21511/im.21\(1\).2025.26](https://doi.org/10.21511/im.21(1).2025.26)

- Saffi, M. A. L. , de M. J. L. J. J. , T. M. M. , P. C. A. , & R.-S. E. R. (2013). *Validity and reliability of a questionnaire on knowledge of cardiovascular risk factors for use in Brazil*.
- Sarkis, N., Jabbour Al Maalouf, N., & El Lakiss, R. (2024). Examining influencer marketing: the roles of para-social relationships, unpaid collaborations, and trustworthiness in shaping consumer buying behavior. *Cogent Business and Management*, 11(1). <https://doi.org/10.1080/23311975.2024.2419501>
- Saunders, M. N. K. ., Lewis, Philip., & Thornhill, Adrian. (2020). *Research methods for business students*. Pearson.
- Suri, A. , H. B. , and S. S. (2023). This Product Seems Better Now: How Social Media Influencers’ Opinions Impact Consumers’ Post-failure Responses. *International Journal of Electronic Commerce*, 27(3), 297-323. .
- Wang, X. (2024). *COLLISION OF BEAUTY: EXPLORING USERS’ PERCEPTIONS OF BEAUTY TRENDS GENERATED BY TIKTOK INFLUENCERS VERSUS DOUYIN INFLUENCERS*.
<https://surface.syr.edu/thesis>
- Yang, Z., Sun, J., Zhang, Y., & Wang, Y. (2015). Understanding SaaS adoption from the perspective of organizational users: A tripod readiness model. *Computers in Human Behavior*, 45, 254–264.
<https://doi.org/10.1016/j.chb.2014.12.022>

APPENDIX A

Survey Questionnaire:

Section 1 of 5

The Influence of Online Trends on Consumer Psychology and Purchasing Decisions in Saudi Customers

☐☐☐☐☐

Dear participant,

This survey is part of a Master's degree research study on how online trends affect consumer psychology and buying decisions in Saudi Arabia. Your participation is voluntary, and all responses will be anonymous and used for academic purposes only.

By continuing, you agree to participate.

After section 1 Continue to next section

Section 2 of 5

Section A: Demographic Information

Description (optional)

Age *

☐ 18–24

☐ 25–34

☐ 35–44

☐ 45–54

☐ 55 or more

Gender *

☐ Female

☐ Male

☐ Other...

Educational Level *

- ☐ High School
- ☐ Diploma
- ☐ Bachelor's Degree
- ☐ Masters Degree or above
- ☐ Other...

Employment Status *

- ☐ Student
- ☐ Employed
- ☐ Unemployed
- ☐ Other...

Monthly Income *

- ☐ Less than 3,000 SAR
- ☐ 3,000–5,999 SAR
- ☐ 6,000–9,999 SAR
- ☐ 10,000 SAR or more
- ☐ Prefer not to say
- ☐ Other...

Section 3 of 5

Section B: Exposure to Online Trends



Please choose or click in the box that best indicates your level of agreement, where

1 2 3 4 5
Strongly Disagree Disagree Neutral Agree Strongly Agree

I often come across trending content on platforms like TikTok or Instagram.

1 2 3 4 5
Strongly Disagree ☐ ☐ ☐ ☐ ☐ Strongly Agree

I follow social media influencers who share trending products or topics.

1 2 3 4 5
Strongly Disagree ☐ ☐ ☐ ☐ ☐ Strongly Agree

I actively engage with viral posts or hashtags.

1 2 3 4 5
Strongly Disagree ☐ ☐ ☐ ☐ ☐ Strongly Agree

Trending content influences what I pay attention to online.

1 2 3 4 5
Strongly Disagree ☐ ☐ ☐ ☐ ☐ Strongly Agree

I am usually aware of what is popular on social media.

1 2 3 4 5
Strongly Disagree ☐ ☐ ☐ ☐ ☐ Strongly Agree

Section 4 of 5

Section C: Psychological Responses



Description (optional)

A. FOMO (Fear of Missing Out)

Description (optional)

I feel anxious when I miss out on popular online trends. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

I try to stay updated so I don't feel left behind. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

Seeing others follow a trend makes me want to join in. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

B. Motivation

Description (optional)

Online trends motivate me to try new products or services. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

I feel encouraged to buy something when I see it trending. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

Trends give me ideas on what to buy. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

C. Emotional Appeal

Description (optional)

Trending content often triggers strong emotional reactions in me. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

I feel excited when I see a product going viral. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

I associate positive feelings with items that are currently trending. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

D. Identity Expression

Description (optional)

Following trends helps me express who I am. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

I buy trending items to feel connected to others. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

Online trends help me shape my personal style or preferences. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

Section D: Purchasing Decisions

Description (optional)

I have bought products because they were trending online. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

I trust products that I see being promoted in trends. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

Trends influence the brands or styles I choose. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

I tend to buy what is currently popular on social media. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree

I compare trending products before making a purchase. *

	1	2	3	4	5	
Strongly Disagree	☐	☐	☐	☐	☐	Strongly Agree