
ADOPTION OF AI-POWERED FOOD DELIVERY PLATFORMS IN THE REPUBLIC OF SERBIA

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ABSTRACT

With the rapid growth of AI technologies, understanding factors driving user adoption of AI-powered platforms is increasingly important. This study investigates factors influencing the adoption of AI-powered food delivery platforms by integrating the Stimulus–Organism–Response framework with Task–Technology Fit theory. Primary research was conducted through a structured questionnaire in May 2024 in the Republic of Serbia, collecting data on communicative competence, technology and task characteristics, perceived intelligence, social influence, anthropomorphism, emotional trust, and task–technology fit. Structural equation modeling tested the hypothesized relationships. Results indicate that both task–technology fit and emotional trust significantly influence adoption intention. The findings highlight the critical roles of emotional trust and effective alignment between technology and user tasks in facilitating adoption of AI platforms in emerging markets. It is recommended that platform providers enhance AI transparency and build user trust. Additional descriptive data reveal moderate AI familiarity among respondents, indicating potential for further user education.

Introduction

The increasing prominence of AI-powered service platforms in the contemporary era has stimulated innovative practices designed to satisfy existing needs and anticipate emerging demands, thereby redefining service delivery and business–customer interactions (Ameen et al., 2021). The retail and food delivery sectors, in particular, are undergoing rapid transformation driven by emerging digital technologies, growing competition, and evolving consumer expectations (Su, 2022; Zhang et al., 2021).

Consumers increasingly interact across multiple channels, prompting service providers to adopt seamless omnichannel strategies and personalized experiences (Cortinas et

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al., 2019; Rodrigues & Brandão, 2020). AI-powered food delivery platforms further support businesses through customer segmentation, targeted marketing, and content optimization, while successful adoption depends on technical expertise, organizational resources, and strategic digital marketing (Yum et al., 2022; Cho et al., 2019; Jia et al., 2020; Sandeep et al., 2022).

In agricultural and food economics, digital transformation drives competitiveness and efficiency across the agri-food value chain (Schroeder et al., 2021). AI-powered food delivery platforms form a growing segment of the digital food economy, connecting producers, restaurants, and consumers through data-driven decision-making (Min et al., 2023). Understanding user adoption is crucial, as technological innovation reshapes distribution, consumer behavior, and market organization, particularly in emerging economies (Trabelsi et al., 2023). This transformation creates opportunities to increase value added, facilitate trade, meet evolving consumer demand, and improve food supply chain efficiency, traceability, and resilience (Schroeder et al., 2021; Ghag et al., 2024).

Despite these advantages, understanding the factors influencing consumer adoption of AI-powered food delivery platforms remains limited. This study examines adoption determinants in the Republic of Serbia, focusing on Task-Technology Fit and Emotional Trust, with the aim of empirically validating the research model and identifying key factors that drive or hinder user acceptance.

Literature Review

Artificial Intelligence (AI) has transformed service industries by extending capabilities for reasoning, problem-solving, and automation (Joiner, 2018). In food delivery, AI-powered platforms use intelligent algorithms, mobile applications, chatbots, and real-time data analysis to optimize operations, personalize services, enhance customer interactions, foster emotional trust, and increase satisfaction and repurchase intentions (Prentice et al., 2020; Adam et al., 2021; Van Esch & Stewart Black, 2021; Ljepava, 2022; Pelau et al., 2021; Maduku et al., 2024; Ameen et al., 2021). Driven by changing consumer behavior and digital reliance, these platforms have transformed meal access through personalized recommendations, tailored menus, and on-demand delivery (Chai & Yat, 2019).

The Stimulus–Organism–Response (S–O–R) framework, originally proposed by Mehrabian and Russell (1974) and later expanded by Jacoby (2002), provides a comprehensive theoretical lens for understanding how external and internal factors shape human behavior through mediating psychological processes. Unlike the traditional Stimulus–Response (S–R) model, which assumes a direct causal link between stimuli and behavior, the S–O–R approach emphasizes the critical role of the organism, representing cognitive and affective evaluations, in translating stimuli into observable behavioral responses (Goi et al., 2014; Alcántara-Pilar et al., 2024).

The Task–Technology Fit (TTF) model, developed by Goodhue and Thompson (1995), complements the S–O–R framework by emphasizing that users are more likely to adopt

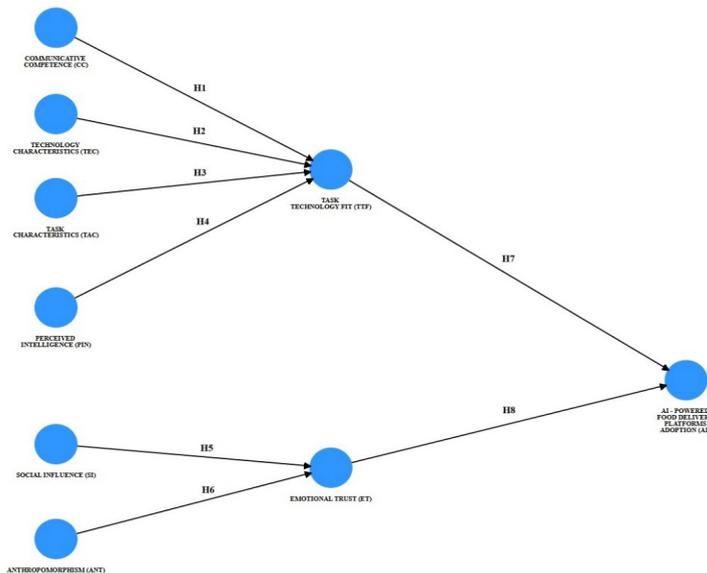
technology when its features align effectively with the tasks they need to accomplish. TTF posits that technology adoption is facilitated when users perceive that a system enhances their ability to complete tasks efficiently and achieve desired outcomes. This perspective has been widely applied in diverse IT contexts, demonstrating that both task characteristics and technology features are significant predictors of user engagement and intention to adopt digital innovations (Vafaei-Zadeh et al., 2023).

Previous research has examined factors influencing the adoption of AI-powered and technology-mediated food delivery platforms. Vafaei-Zadeh et al. (2023) integrated the SOR and TTF frameworks for AI customer service adoption, while other studies explored gamification in mobile delivery (Liao & Ahn, 2025), drone-based delivery (Abbasi et al., 2024), and customer inspiration via the SOR paradigm (Malik et al., 2024). Additionally, Saygıner (2024) studied customer satisfaction and loyalty during and after COVID-19, Shorbaji et al. (2025) reviewed AI-enabled food-ordering apps, and Leung et al. (2025) analyzed young adults' consumption behavior, collectively highlighting technological, psychological, and contextual factors in AI-driven food delivery adoption.

Research model

In this study, the S–O–R model from Vafaei-Zadeh et al. (2023), originally used for AI customer service adoption, is applied to AI-powered food delivery platforms in the Republic of Serbia. The focus is on how external stimuli, such as communicative competence, technology and task characteristics, perceived intelligence, social influence, and anthropomorphism, affect internal evaluations, including task-technology fit and emotional trust, which in turn influence adoption. The conceptual model is shown in Figure 1.

Figure 1. Conceptual Model of AI-Powered Food Delivery Platforms Adoption



Source: Author (2025)

Based on the S–O–R model and TTF theory, eight hypotheses were formulated to investigate platforms adoption, each grounded in theoretical rationale (Vafaei-Zadeh et al., 2023). Together, these hypotheses provide a comprehensive framework for understanding the factors shaping user perceptions, emotional trust, and adoption of AI-powered food delivery platforms.

H1: *Communicative competence positively influences task-technology fit in AI-powered food delivery platforms.*

Communicative competence in AI chatbots refers to their ability to provide clear, timely, and relevant responses that resemble human communication. Such competence enhances user satisfaction and task–technology fit, thereby strengthening acceptance of AI solutions.

H2: *Technology characteristics positively influence task-technology fit in AI-powered food delivery platforms.*

Technology characteristics refer to key attributes of AI tools, including personalization, real-time information, availability, and ease of use. When these features align with user needs, task–technology fit improves, enhancing effectiveness and acceptance of AI services and promoting user adoption.

H3: *Task characteristics positively influence task-technology fit in AI-powered food delivery platforms.*

Task characteristics refer to the nature and complexity of activities users perform when interacting with a service. When these requirements align with the technology’s features, task–technology fit improves, enhancing ease of use and promoting user acceptance of AI-based solutions.

H4: *Perceived intelligence positively influences task-technology fit in AI-powered food delivery platforms.*

Perceived intelligence refers to a system’s ability to perform tasks effectively, learn from interactions, and respond appropriately to user needs. In AI-powered services, higher perceived intelligence, demonstrated through responsiveness, problem-solving, and adaptability, enhances task-technology fit and encourages user adoption.

H5: *Social influence positively influences emotional trust in AI-powered food delivery platforms.*

Social influence reflects the extent to which individuals perceive that important others expect them to adopt new technology. Recommendations from family, friends, or colleagues are often seen as more trustworthy, and social influence helps build emotional trust in human-AI interactions.

H6: *Anthropomorphism positively influences emotional trust in AI-powered food delivery platforms.*

Anthropomorphism involves attributing human-like characteristics, emotions, or behaviors to AI systems. This can make interactions feel more natural and strengthen emotional connections, though research shows mixed effects on emotional trust, ranging from positive to limited or negative.

H7: *Task-technology fit positively influences AI-powered food delivery platform adoption.*

Task-technology fit refers to how well a technology’s capabilities align with the requirements of a specific task, affecting its perceived usefulness. Strong alignment enhances performance and efficiency, increasing the likelihood of adoption, while poor alignment reduces it, emphasizing the need to match technology features with task demands.

H8: *Emotional trust positively influences AI-powered food delivery platform adoption.*

Emotional trust reflects a user’s confidence and comfort in relying on a technology, influencing their willingness to adopt it. In AI-powered services, users are more likely to engage with systems that provide emotional security and positive experiences, which strongly drive adoption intentions.

Methodology

The primary research employed a convenience sample and was conducted through a structured questionnaire in May 2024 in the Republic of Serbia, encompassing a total of 392 respondents—users of food delivery platforms who are aware that the platform employs artificial intelligence. The questionnaire was distributed online through various channels to reach a diverse group of participants. The questionnaire was structured in two sections. The first section collected respondents’ demographic and background information, including age, gender, education level, platforms usage frequency, ordering frequency, self-assessed AI knowledge, and perception of whether food delivery platforms use AI (Table 1). The second section assessed participants’ perceptions across multiple items for each research construct, using a five-point Likert scale (1 - “strongly disagree” to 5 - “strongly agree”).

Table 1. Demographic and Background Characteristics of Sample

Category	Percentage (%)
Age	
18-24	24.5
25-34	38.0
35-44	22.2
45-54	10.7
55 and above	4.6
Gender	
Male	40.8
Female	59.2

Category	Percentage (%)
Education Level	
High School Diploma	16.6
College of Applied Studies Diploma	12.2
Bachelor's Degree	37.2
Master's Degree	32.9
Doctoral Degree (PhD)	1.0
Platforms Usage Frequency	
Regularly	23.5
Occasionally	76.5
Ordering Frequency	
Daily	10.5
Weekly	20.9
Monthly	28.8
Less often	39.8
Self-Assessed AI Knowledge	
Very low	1.5
Low	23.7
Moderate	37.2
High	33.7
Very high	3.8
Belief That Food Delivery Platforms Use AI	
Certain	54.1
Believes so but unsure	45.9

Source: Author (2025)

Platforms used included Wolt, Glovo, Mister D, restaurant websites/apps, and Office Bite, with Wolt and Glovo most popular. Most respondents identified AI use for predicting delivery times, personalized promotions and discounts, and automated meal recommendations, while fewer recognized AI in image recognition and visual food search or voice interaction and chatbots.

The statistical model comprises eight constructs: Communicative Competence (CC), Technology Characteristics (TEC), Task Characteristics (TAC), Perceived Intelligence (PIN), Social Influence (SI), Anthropomorphism (ANT), Task-Technology Fit (TTF), and AI-powered Food Delivery Platforms Adoption (AD). All indicators were adapted from Vafaei-Zadeh et al. (2024) to fit the context of AI-powered food delivery platforms (Table 2).

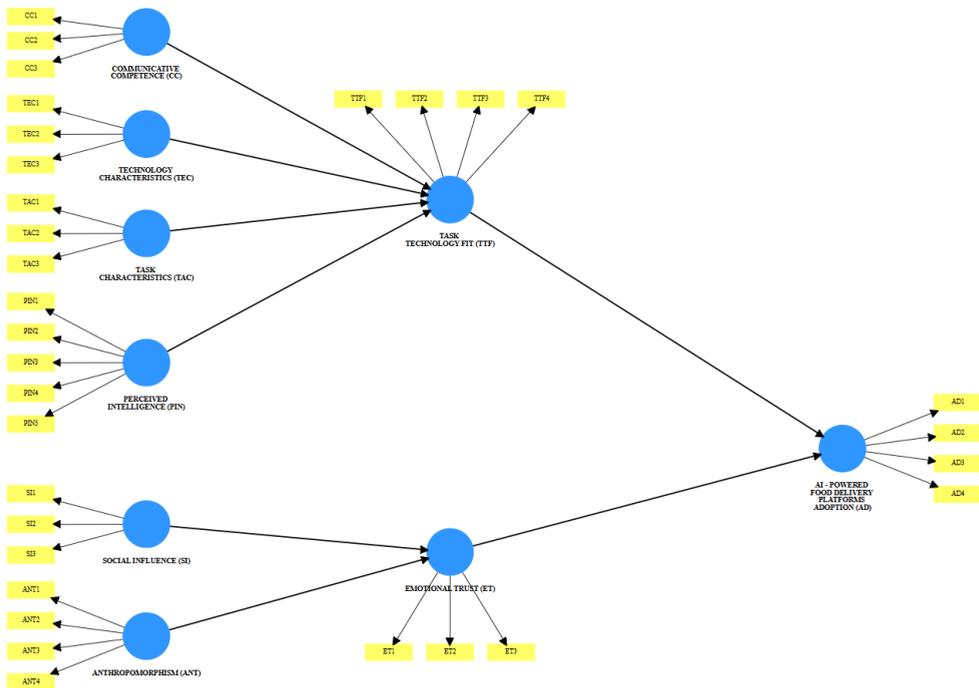
Table 2. Constructs and Indicators (Items)

CONSTRUCTS		INDICATORS (ITEMS)
COMMUNICATION COMPETENCE (CC)	CC1	AI-powered food delivery platforms will be more productive than face-to-face interactions with in-store agents.
	CC2	Communication through AI-powered food delivery platforms will be more efficient than other forms of communication for ordering food.
	CC3	AI-powered food delivery platforms will save a tremendous amount of time.
TECHNOLOGY CHARACTERISTICS (TEC)	TEC1	AI-powered food delivery platforms will provide ubiquitous service.
	TEC2	AI-powered food delivery platforms will provide real-time service.
	TEC3	AI-powered food delivery platforms will provide secure service.
TASK CHARACTERISTICS (TAC)	TAC1	I will need to access my food delivery inquiries anytime, anywhere.
	TAC2	I will need to send my food delivery inquiries anytime, anywhere.
	TAC3	I will need to receive my food delivery inquiry responses in real-time.
PERCEIVED INTELLIGENCE (PIN)	PIN1	AI-powered food delivery platforms will be able to complete tasks quickly.
	PIN2	AI-powered food delivery platforms will understand my commands.
	PIN3	AI-powered food delivery platforms will be able to communicate with me in an understandable manner.
	PIN4	AI-powered food delivery platforms will be able to find and process the necessary information for completing their tasks.
	PIN5	AI-powered food delivery platforms will provide useful answers.
TASK-TECHNOLOGY FIT (TTF)	TTF1	The functionalities of AI-powered food delivery platforms will be very adequate.
	TTF2	The functionalities of AI-powered food delivery platforms will be very appropriate.
	TTF3	The functionalities of AI-powered food delivery platforms will be very sufficient.
	TTF4	The functions of AI-powered food delivery platforms will fully meet my ordering and support needs.

CONSTRUCTS		INDICATORS (ITEMS)
SOCIAL INFLUENCE (SI)	SI1	Many people I know will use AI-powered food delivery services.
	SI2	People who influence my behavior will use AI-powered food delivery services.
	SI3	People whose opinions I value will use AI-powered food delivery services.
ANTHROPOMORPHISM (ANT)	ANT1	It is important that the conversation with AI-powered food delivery platforms resembles one with a human being.
	ANT2	Conversations with AI-powered food delivery platforms should be natural.
	ANT3	AI-powered food delivery platforms should seem as if they understand the person with whom they are interacting.
	ANT4	Conversation with the AI-powered food delivery platforms should not be artificial.
EMOTIONAL TRUST (ET)	ET1	I will feel secure relying on AI-powered food delivery platforms for inquiries.
	ET2	I will feel comfortable trusting AI-powered food delivery platforms for assistance.
	ET3	I will be satisfied relying on AI-powered food delivery platforms for support.
AI – POWERED FOOD DELIVERY PLATFORMS ADOPTION (AD)	AD1	I will be interested in using AI-powered food delivery platforms.
	AD2	AI-powered food delivery platforms will increase my willingness to use it.
	AD3	I will recommend AI-powered food delivery platforms to others.
	AD4	I will use this AI-powered food delivery platforms for ordering and assistance.

Source: Author (2025)

Each variable was modeled as a reflective construct (Figure 2), meaning the individual items are highly similar. Given the latent nature of the variables, Partial Least Squares Structural Equation Modeling (PLS-SEM) was used to test the hypotheses. PLS-SEM combines regression and factor analysis techniques, making it suitable for analyzing latent constructs measured indirectly through indicators (Sarstedt, Ringle, & Hair, 2021).

Figure 2. Statistical Model of AI-Powered Food Delivery Platforms Adoption

Source: Author (2025)

The questionnaire was pretested, and given the reflective nature of all constructs, reliability, convergent validity, and discriminant validity were assessed. Reliability was evaluated using Cronbach's alpha and composite reliability (CR), convergent validity with average variance extracted (AVE), and discriminant validity using the Fornell–Larcker criterion and the HTMT ratio (Grubor et al., 2021). Following Hair, Risher, Sarstedt, and Ringle (2019), reflective constructs were assessed by:

- Outer loadings – values above 0,7 indicating indicator reliability;
- Internal consistency – Cronbach's α , CR, and ρ_A between 0,70 and 0,95 considered satisfactory;
- Convergent validity – $AVE \geq 0,50$; and
- Discriminant validity – HTMT ratios below 0,85.

The structural model was then analyzed, examining path coefficients and their significance levels. All analyses were conducted using SmartPLS 4 (Grubor et al., 2021).

Results and Discussions

Measurement Model

Reliability of the indicators in the AI-powered food delivery platforms adoption model was first assessed through outer loadings (Table 3). All first-order reflective construct indicators exceeded the 0,70 threshold, except for PIN4 (AI-powered food delivery platforms will be able to find and process the necessary information for completing their tasks) and TTF3 (The functionalities of AI-powered food delivery platforms will be very sufficient), which were excluded, leading to a revised model for subsequent analysis.

Table 3. Indicator Reliability – Outer Loadings

	AI - POWERED FOOD DELIVERY PLATFORMS ADOPTION (AD)	ANTHROPOMORPHISM (ANT)	COMMUNICATIVE COMPETENCE (CC)	EMOTIONAL TRUST (ET)	PERCEIVED INTELLIGENCE (PIN)	SOCIAL INFLUENCE (SI)	TASK CHARACTERISTICS (TAC)	TASK-TECHNOLOGY FIT (TTF)	TECHNOLOGY CHARACTERISTICS (TEC)
AD1	0,839								
AD2	0,884								
AD3	0,922								
AD4	0,870								
ANT1		0,798							
ANT2		0,773							
ANT3		0,829							
ANT4		0,773							
CC1			0,867						
CC2			0,758						
CC3			0,829						
ET1				0,876					
ET2				0,899					
ET3				0,836					
PIN1					0,721				
PIN2					0,808				
PIN3					0,794				
PIN4					0,605				
PIN5					0,778				
SI1						0,838			
SI2						0,893			
SI3						0,884			
TAC1							0,868		

	AI - POWERED FOOD DELIVERY PLATFORMS ADOPTION (AD)	ANTHROPOMORPHISM (ANT)	COMMUNICATIVE COMPETENCE (CC)	EMOTIONAL TRUST (ET)	PERCEIVED INTELLIGENCE (PIN)	SOCIAL INFLUENCE (SI)	TASK CHARACTERISTICS (TAC)	TASK-TECHNOLOGY FIT (TTF)	TECHNOLOGY CHARACTERISTICS (TEC)
TAC2							0,924		
TAC3							0,830		
TEC1									0,824
TEC2									0,828
TEC3									0,865
TTF1								0,840	
TTF2								0,849	
TTF3								0,690	
TTF4								0,759	

Source: Author (2025)

The results of testing internal consistency and convergent validity are presented in Table 4. All constructs showed Cronbach's alpha values above 0,7, with CR values ranging from 0,7 to 0,95, indicating satisfactory reliability and internal consistency. AVE values exceeded the recommended threshold of 0,5, and all indicator outer loadings surpassed 0,7, confirming the convergent validity of the constructs.

Table 4. Outer Loadings of Indicators

Constructs and Items	Outer Loadings	Cronbach's Alpha Coefficients	CR	AVE
COMMUNICATION COMPETENCE - CC		0,754	0,774	0,671
CC1	0,867			
CC2	0,758			
CC3	0,829			
TECHNOLOGY CHARACTERISTICS - TEC		0,793	0,813	0,704
TEC1	0,824			
TEC2	0,828			
TEC3	0,865			
TASK CHARACTERISTICS - TAC		0,846	0,849	0,765
TAC1	0,868			
TAC2	0,924			
TAC3	0,830			

Constructs and Items	Outer Loadings	Cronbach's Alpha Coefficients	CR	AVE
PERCEIVED INTELLIGENCE - PIN		0,797	0,803	0,622
PIN1	0,721			
PIN2	0,808			
PIN3	0,794			
PIN5	0,778			
TASK-TECHNOLOGY FIT - TTF		0,792	0,798	0,708
TTF1	0,840			
TTF2	0,849			
TTF4	0,759			
SOCIAL INFLUENCE - SI		0,842	0,851	0,760
SI1	0,838			
SI2	0,893			
SI3	0,884			
ANTHROPOMORPHISM - ANT		0,806	0,821	0,630
ANT1	0,798			
ANT2	0,773			
ANT3	0,829			
ANT4	0,773			
EMOTIONAL TRUST - ET		0,841	0,851	0,759
ET1	0,876			
ET2	0,899			
ET3	0,836			
AI – POWERED FOOD DELIVERY PLATFORMS ADOPTION - AD		0,902	0,904	0,773
AD1	0,839			
AD2	0,884			
AD3	0,922			
AD4	0,870			

Source: Author (2025)

Discriminant validity was assessed using the results presented in Table 5. The square root of the AVE for each construct exceeded its correlations with other constructs, providing clear evidence of discriminant validity. The Fornell–Larcker criterion showed no issues, further confirming the constructs' discriminant validity.

Table 5. Discriminant Validity of Constructs – Fornell–Larcker Criterion

	AI - POWERED FOOD DELIVERY PLATFORMS ADOPTION (AD)	ANTHROPOMORPHISM (ANT)	COMMUNICATIVE COMPETENCE (CC)	EMOTIONAL TRUST (ET)	PERCEIVED INTELLIGENCE (PIN)	SOCIAL INFLUENCE (SI)	TASK CHARACTERISTICS (TAC)	TASK-TECHNOLOGY FIT (TTF)	TECHNOLOGY CHARACTERISTICS (TEC)
AI - POWERED FOOD DELIVERY PLATFORMS ADOPTION (AD)	0,879								
ANTHROPOMORPHISM (ANT)	0,369	0,794							
COMMUNICATIVE COMPETENCE (CC)	0,519	0,315	0,819						
EMOTIONAL TRUST (ET)	0,587	0,427	0,630	0,871					
PERCEIVED INTELLIGENCE (PIN)	0,619	0,529	0,436	0,615	0,789				
SOCIAL INFLUENCE (SI)	0,262	0,296	0,365	0,332	0,243	0,872			
TASK CHARACTERISTICS (TAC)	0,360	0,372	0,444	0,434	0,358	0,336	0,875		
TASK-TECHNOLOGY FIT (TTF)	0,690	0,401	0,590	0,595	0,668	0,387	0,441	0,841	
TECHNOLOGY CHARACTERISTICS (TEC)	0,601	0,401	0,640	0,664	0,572	0,290	0,478	0,644	0,839

Source: Author (2025)

The establishment of discriminant validity was further confirmed using the HTMT approach, where the HTMT ratio for each pair of constructs was below the threshold of 0,85 (Table 6), indicating the absence of multicollinearity and confirming discriminant validity among the constructs.

Table 6. Discriminant Validity of Constructs – HTMT Criterion

	AI - POWERED FOOD DELIVERY PLATFORMS ADOPTION (AD)	ANTHROPOMORPHISM (ANT)	COMMUNICATIVE COMPETENCE (CC)	EMOTIONAL TRUST (ET)	PERCEIVED INTELLIGENCE (PIN)	SOCIAL INFLUENCE (SI)	TASK CHARACTERISTICS (TAC)	TASK-TECHNOLOGY FIT (TTF)	TECHNOLOGY CHARACTERISTICS (TEC)
AI - POWERED FOOD DELIVERY PLATFORMS ADOPTION (AD)									
ANTHROPOMORPHISM (ANT)	0,417								
COMMUNICATIVE COMPETENCE (CC)	0,629	0,399							
EMOTIONAL TRUST (ET)	0,665	0,508	0,793						
PERCEIVED INTELLIGENCE (PIN)	0,729	0,664	0,571	0,753					
SOCIAL INFLUENCE (SI)	0,297	0,340	0,437	0,387	0,301				
TASK CHARACTERISTICS (TAC)	0,414	0,454	0,546	0,521	0,437	0,389			
TASK-TECHNOLOGY FIT (TTF)	0,818	0,495	0,755	0,723	0,835	0,476	0,537		
TECHNOLOGY CHARACTERISTICS (TEC)	0,691	0,500	0,830	0,806	0,705	0,347	0,587	0,793	

Source: Author (2025)

These findings, confirming the reliability and validity of the measurement indicators, provide the foundation for structural model analysis. This analysis tests the hypothesized relationships among latent constructs, identifies key factors influencing the phenomenon, and quantitatively assesses the strength of these effects.

Structural Model

To assess the path coefficients in the study, the bootstrapping procedure with 10.000 subsamples was applied, as presented in Table 7, all obtained path coefficients were statistically significant with p-values below 0,05, indicating a positive influence of the analyzed factors on the adoption of AI-powered food delivery platforms.

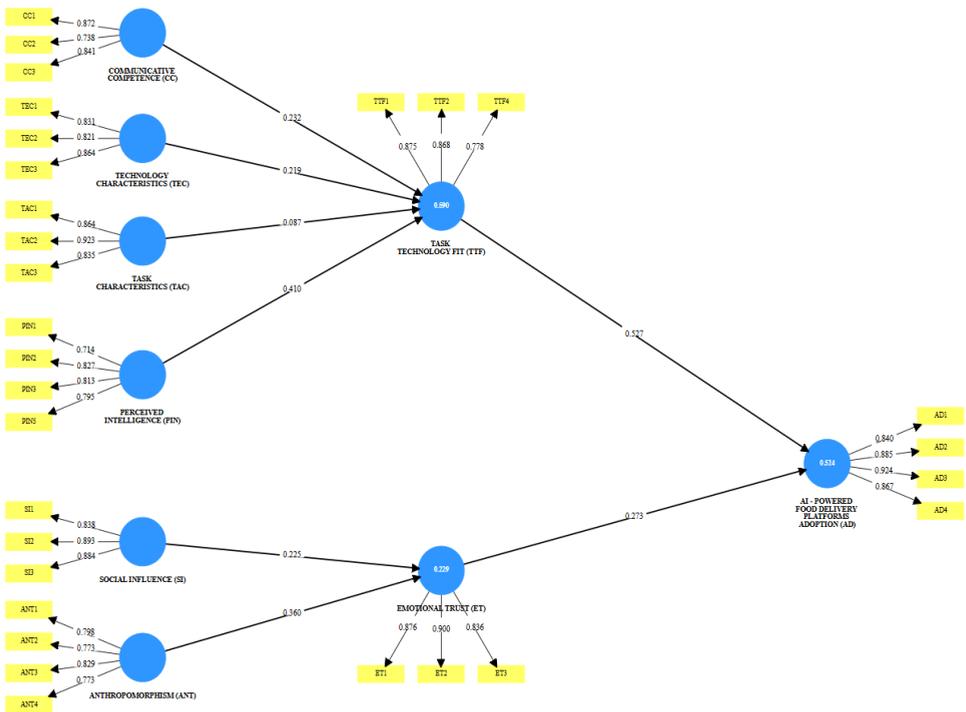
Table 7. Testing of Second-Order Constructs

Relationships	Path Coefficients	Standard Deviation	T Statistics	P Value	VIF Value
Communicative Competence → Task-Technology Fit	0,232	0,044	5,265	0,000	1,781
Technology Characteristics → Task-Technology Fit	0,219	0,052	4,249	0,000	2,168
Task Characteristics → Task-Technology Fit	0,087	0,041	2,107	0,035	1,365
Perceived Intelligence → Task-Technology Fit	0,410	0,040	10,220	0,000	1,520
Social Influence → Emotional Trust	0,225	0,055	4,124	0,000	1,096
Anthropomorphism → Emotional Trust	0,360	0,056	6,476	0,000	1,096
Task-Technology Fit → AI – Powered Food Delivery Platforms Adoption	0,527	0,043	12,321	0,000	1,549
Emotional Trust → AI – Powered Food Delivery Platforms Adoption	0,273	0,046	5,897	0,000	1,549

Source: Author (2025)

The structural model (Figure 3) indicates that all lower-order constructs significantly contribute to higher-order constructs. Perceived Intelligence has the largest impact on Task-Technology Fit (0,410), followed by Communicative Competence (0,232), Technology Characteristics (0,219), and Task Characteristics (0,087). For Emotional Trust, Anthropomorphism (0,360) and Social Influence (0,225) are significant. Task-Technology Fit (0,527) and Emotional Trust (0,273) strongly influence the adoption of AI-powered food delivery platforms. The results show no multicollinearity among the factors, as all VIF values are below 5. Perceived Intelligence (1,520), Communicative Competence (1,781), Technology Characteristics (2,168), and Task Characteristics (1,365) significantly affect Task-Technology Fit ($p < 0,05$), while Social Influence (1,096) and Anthropomorphism (1,096) significantly affect Emotional Trust ($p < 0,05$), supporting the applicability of the S–O–R framework in explaining the adoption of AI-powered food delivery platforms.

Figure 3. Structural Model



Source: Authors' calculations (2025)

The results are generally consistent with previous empirical findings, including the research of Vafaei-Zadeh et al. (2023), which demonstrated that social influence and anthropomorphism substantially affect emotional trust. Similar to their conclusions, the positive role of social networks can be interpreted through social proof and peer endorsement mechanisms that strengthen affective confidence in AI technologies (Chi et al., 2021; Shi et al., 2021). The identified impact of anthropomorphism confirms that human-like attributes of AI interfaces enhance user comfort and the perception of natural interaction (Lee & Chen, 2022).

Communicative competence and perceived intelligence are revealed as essential determinants of perceived task–technology fit, supporting earlier evidence that natural communication and adaptive learning capabilities increase the perceived adequacy of AI systems for user tasks (Song et al., 2022; Pillai & Sivathanu, 2020). In this context, effective interpretation of informal dialogue and the ability to provide personalized recommendations are perceived as key aspects of technological fit. Although task characteristics show a weaker direct effect, the strong relationship between task–technology fit and adoption differs slightly from the results of Vafaei-Zadeh et al. (2023), where this path was not always significant. This discrepancy may stem from the specific context of food delivery services, in which functional efficiency and perceived usefulness have a more immediate impact on behavioral intention.

The obtained results indicate that both task–technology fit and emotional trust play a significant role in the intention to adopt AI-powered food delivery platforms. All indicators showed a positive and statistically significant effect on adoption intention, confirming support for all eight proposed hypotheses. This highlights that Task-Technology Fit and Emotional Trust strongly drive adoption, while Communicative Competence, Technology Characteristics, Task Characteristics, Perceived Intelligence, Social Influence, and Anthropomorphism act as key antecedents.

These findings extend the understanding of AI adoption in the context of agricultural and food economics in the Republic of Serbia. Greater alignment between task and technology, along with emotional trust, can reduce transaction costs, improve supply-chain coordination, and expand market access for small producers (Schroeder et al., 2021; Min et al., 2023). For sustainable digital transformation, platform developers should prioritize intelligent, adaptive, and transparent AI functions that enhance user confidence and operational efficiency. Public policy and educational initiatives that promote digital literacy and trust in AI can further support equitable technological adoption in agricultural and food service markets. By providing evidence from an emerging market, this study offers practical insights for policymakers and platform developers seeking to optimize AI adoption and strengthen competitiveness in the regional agri-food sector.

Conclusions

This study combines the Stimulus–Organism–Response framework with Task–Technology Fit theory to examine AI-powered food delivery platforms adoption in the Republic of Serbia. It shows how stimuli such as Communicative Competence, Technology and Task Characteristics, Perceived Intelligence, Social Influence, and Anthropomorphism affect Task-Technology Fit and Emotional Trust, which in turn drive adoption, highlighting the importance of aligning technology with tasks and fostering emotional trust.

Empirical findings show that Perceived Intelligence is the strongest determinant of Task-Technology Fit, with Communicative Competence, Technology Characteristics, and Task Characteristics also contributing positively. Anthropomorphism and Social Influence enhance Emotional Trust, and together, Task-Technology Fit and Emotional Trust significantly influence adoption intentions, highlighting the importance of both cognitive and emotional factors in AI service platform acceptance. These results have practical implications for service providers seeking to optimize AI-powered food delivery platforms. Prioritizing AI systems that balance efficiency, task alignment, and human-like interaction can increase user satisfaction, trust, and engagement. Features such as real-time updates, personalized recommendations, intuitive conversational interfaces, and socially endorsed functionalities can strengthen both task efficacy and emotional connection, ultimately driving sustained adoption. From the perspective of agricultural and food economics, these insights suggest that well-designed AI platforms can enhance operational efficiency, improve supply chain coordination, and expand market access, supporting the broader goals of competitiveness and innovation in the agri-food sector.

Future research could expand the proposed model to capture additional dimensions of consumer behavior and further validate its applicability in different contexts. Longitudinal designs may also be employed to observe how adoption intentions evolve over time as AI technologies advance. In addition, qualitative approaches could complement survey-based methods by offering deeper insights into consumer perceptions and trust in AI-powered services.

Conflict of interests

The author declares no conflict of interest.

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