

Risks related to Artificial Intelligence in service experience: a bibliometric analysis and development of a conceptual framework for the premium service context

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(Submitted: 25 July, 2026; Accepted: 22 September, 2026)

Abstract: The integration of artificial intelligence (AI) into service touchpoints both enhances efficiency and personalization capabilities and creates risks that can degrade the premium service experience. This study identifies the knowledge structure, the level of development of topics, and the mechanisms of risk formation related to AI, thereby proposing a conceptual framework connecting AI risks, trust, and experiential value. Data comprises 390 publications collected from Web of Science from 2021 to June 20, 2026. Bibliometrix/Biblioshiny was used for descriptive statistics, keyword co-occurrence analysis, topic mapping, and co-citation analysis of relationships among documents, authors, and keywords. The results show that the cluster of trust, acceptance, and intention holds a prominent position, while tourism, technology, and hospitality form the contextual foundation of the sector. This conceptual synthesis identifies four risk mechanisms: algorithmic lack of transparency, data and privacy asymmetry, diminished control, and dehumanization of the experience. Drawing on conservation of resources (COR) theory and a customer journey approach, the study proposes trust as a theoretical mediating mechanism between AI risk and experiential value. The results contribute to connecting fragmented research streams and provide a basis for customer-centric AI governance in premium services.

Keywords: artificial intelligence, perceived risk, trust, experiential value, premium services

1. Introduction

Artificial intelligence (AI) is transforming how businesses design, deliver, and manage service experiences. Applications such as recommendation systems, chatbots, virtual assistants, customer recognition, predictive analytics, and service robots enable process automation, personalized interactions, and real-time responses to customer needs (Huang & Rust, 2018, 2021). Unlike traditional support technologies, AI has the ability to learn from data, make predictions, and directly participate in service decisions. Therefore, AI not only improves operational efficiency but also restructures the roles of customers, employees, and technology at touchpoints in the customer journey.

This shift is particularly important in premium services, where customer value is determined not only by functional outcomes but also by personalization, uniqueness, discretion, a sense of being respected, and the symbolic significance of the experience (Holbrook, 1999; Kapferer & Bastien, 2012). In this study, premium

service is understood as contexts with high levels of financial, emotional, or symbolic investment, coupled with superior expectations for interaction quality and individual responsiveness. AI can help businesses predict demand and deliver more consistent service, but excessive automation can also diminish the human presence and the feeling of being recognized as a unique customer.

Alongside its benefits, AI also gives rise to risks related to lack of transparency, privacy, control, and the dehumanization of service interactions. Customers may not know what data is being collected, how algorithms are using that data, or why a particular service recommendation or decision is being made (Acquisti et al., 2015; Burrell, 2016). In the service-hospitality context, AI devices capable of observing or collecting data can also increase privacy concerns and customer insecurity (Hu & Min, 2023). When AI replaces or mediates tasks previously performed by employees, customers may feel the experience lacks empathy and social recognition (Mende et al., 2019).

Much of previous research on AI in service has focused on operational efficiency, usefulness, technology adoption, and usage intentions. Several studies have examined algorithmic aversion, privacy concerns, service robots, and customer vulnerability (Castelo et al., 2019; Longoni et al., 2019). However, results are scattered across research streams and limited in explaining how AI-related risks are generated, accumulated, and interpreted throughout the customer journey. In particular, there is a need for further clarification on how these risk mechanisms relate to trust and experiential value in the context of premium services.

This gap necessitates a shift from viewing AI as a technical tool to viewing it as an active participant in creating experiences. According to the customer journey approach, experiences are formed through a series of touchpoints before, during, and after the service, rather than being evaluated only at the point of transaction completion (Lemon & Verhoef, 2016). An early AI interaction can influence expectations, feelings of security, and how customers interpret subsequent interactions. AI risk, therefore, needs to be viewed as a process phenomenon, capable of changing and accumulating along the customer journey.

This research applies the conservation of resources (COR) theory to explain this process. According to COR, individuals tend to seek, maintain, and protect resources that they value. The risk of resource loss or depletion can create stress (Hobfoll, 1989, 2001; Hobfoll et al., 2018). In AI-powered services, lack of transparency, excessive data collection, reliance on algorithms, or a decline in human interaction can be interpreted by customers as threats to privacy, control, psychological safety, and a sense of recognition.

Based on this, the study proposes that trust is the theoretical mediating mechanism connecting AI risk with experiential value. Trust reflects the willingness to accept a state of vulnerability based on the expectation that the system and the business providing the service will act competently, ethically, and in good faith (Mayer et al., 1995). When trust declines, customers may have to dedicate more resources to monitoring the system, scrutinizing decisions, or seeking employee intervention; this can diminish experiential value even if the AI remains functionally effective.

The study combines bibliometric analysis with process-based conceptual synthesis. Bibliometric analysis uses a broader set of publications on AI and service experience to identify the knowledge structure of the domain; based on this, conceptual synthesis extrapolates and applies risk mechanisms to the high-end service context. The study answers four questions:

RQ1: How is the knowledge structure of research on AI and service experience formed?

RQ2: How are the main research topics distributed and developed within the knowledge structure of the field?

RQ3: What mechanisms give rise to perceived AI-related risk in the service experience journey?

RQ4: How can trust connect AI risk to experiential value in the context of premium services?

The research contributes in three ways. First, it systematizes the knowledge structure and scattered thematic clusters regarding AI in service experiences. Second, combining COR with a customer journey approach provides a basis for explaining AI risk as a process that threatens resources, rather than simply a consequence of technological failure. Third, the research proposes a conceptual framework in which trust is the theoretical mediating mechanism between AI risk and experiential value, thereby providing a foundation for empirical research and for customer-centric AI governance in premium services.

2. Theoretical background and literature review

2.1. Premium service experience from a customer journey approach

Service experience is formed from the totality of cognitive, emotional, behavioral, and social responses of customers during their interaction with the business. Experience is not only the result at the point of consumption but develops through a series of touchpoints before, during, and after the service (Lemon & Verhoef, 2016). Therefore, the same technology can be evaluated differently by customers depending on the stage of the journey, interaction goals, and previously accumulated experiences.

Within the scope of this study, premium service is understood as service contexts with a high level of financial, emotional, or symbolic investment, where customers expect superior quality, personalization, uniqueness, discretion, and a feeling of being recognized as a distinct individual. The value of premium service therefore lies not only in fulfilling its function correctly but also in how the service is delivered and the meaning customers attach to the entire experience (Holbrook, 1999; Kapferer & Bastien, 2012).

The integration of AI can enhance the experience through the ability to predict needs, personalize recommendations, and shorten response times. However, these benefits may come with a decrease in human interaction, an increased feeling of being monitored, or a standardization of the experience. This paradox is particularly evident in premium service: the more the technology is able to recognize and predict needs, the more customers may care about how their data is collected, processed, and used.

2.2. Experiential value in premium services

Service quality and experiential value are two related but not identical concepts. Service quality primarily reflects customers' assessments of the excellence and reliability of the service delivery process. Meanwhile, experiential value is a comprehensive assessment of the benefits customers receive compared to the costs and trade-offs throughout the entire service journey (Zeithaml, 1988; Holbrook, 1999).

Within the scope of this study, experiential value in premium services is summarized through five aspects. Functional value is expressed in accuracy, convenience, and efficiency; emotional value is associated with comfort, peace of mind, and enjoyment; relational value is expressed in the feeling of being listened to, understood, and respected; symbolic value is associated with uniqueness, status, and self-expression; and control value reflects the customer's choice and proactive ability in service interaction.

AI can increase functional value but simultaneously diminish emotional, relational, symbolic, or controllable value. For example, an automated check-in process might be fast and accurate but still be undervalued if customers feel unwelcome or unable to request assistance from staff when needed. Therefore, the technical efficiency of AI does not automatically translate into positive experiential value.

The study uses experiential value as its central outcome because this concept more fully reflects the multifaceted impact of AI than single indicators such as satisfaction or intention to continue using the service. Experiential value is formed and adjusted throughout the customer journey, based on how customers weigh the benefits offered by AI and the resources they may have to sacrifice.

2.3 Perceived risk in AI from the perspective of Conservation of Resources (COR) Theory

Perceived risk reflects a customer's subjective assessment of the likelihood of undesirable outcomes and the severity of those outcomes (Bauer, 1960; Mitchell, 1999). Perceived risk does not necessarily stem from an actual incident. If a customer simply doesn't understand how the system operates or feels unable to control the consequences, a perception of risk can already form.

This characteristic is relevant to the AI context because the operation of algorithms often cannot be directly observed or interpreted by the customer. A customer might receive a suitable proposal but still be concerned about the amount of data used to generate it. Similarly, an automated decision might be correct but still produce a negative reaction if the customer is not given an explanation or the opportunity to request a human review.

This study applies the conservation of resources (COR) theory to explain the formation of perceived risk. According to COR, individuals tend to seek, maintain, and protect resources they value. The risk of losing resources, actual losses, or investing resources without achieving desired results can all create stress (Hobfoll, 1989, 2001; Hobfoll et al., 2018).

Applying COR to the context of AI-powered services, this study outlines six groups of resources that customers may perceive as being threatened: control resources, related to the right to choose, refuse, or request human intervention; information resources, linked to privacy and the ability to control personal data; time and effort resources, reflected in the ability to access services without having to deal with complex technological processes; psychological resources, including feelings of security, certainty, and predictability; Relational resources, manifested in feelings of being heard, respected, and treated fairly; and symbolic resources, associated with the identity, status, and uniqueness of the premium experience.

From a COR perspective, AI becomes a source of perceived risk when customers believe that the technology may threaten or degrade these resources. This interpretation extends risk research from the scope of technical errors to the cognitive, emotional, relational, and symbolic consequences in the service experience.

2.4 Trust and reliability in AI-Powered services

Trust and reliability are closely related but not identical. Reliability reflects the attributes of the trusted entity, with competence, goodwill, and integrity being three important foundations for trust formation. Trust is a psychological state expressing a willingness to accept vulnerability based on positive expectations about the behavior of the trusted entity (Mayer et al., 1995).

In interactions with automated technology, trust guides the degree to which customers are willing to rely on the system, especially when the technology's operation is complex and cannot be fully understood by

the user (Lee & See, 2004). For AI, trust also depends on the system's characteristics, how the system behaves in interaction, and the organizational context in which the technology is deployed (Glikson & Woolley, 2020).

In AI-powered services, this study distinguishes between two objects of trust. First, the AI system, in terms of its capabilities, stability, predictive ability, and data processing. Second, the service provider, in terms of goodwill, responsibility, integrity, and how the company deploys, monitors, and manages the AI. This distinction is necessary because customers evaluate not only the performance of the technology but also the accountability of the company behind it (Mayer et al., 1995; Lee & See, 2004; Glikson & Woolley, 2020).

A system may function correctly from a technical standpoint but still fail to inspire trust if customers believe the company collects excessive data or is not accountable for automated decisions. Conversely, the credibility, goodwill, and accountability of the company can help customers accept a certain degree of uncertainty when interacting with AI. Therefore, trust in AI-powered services is seen as a structure comprising two related but distinct entities: trust in the AI system and trust in the business that deploys and manages that system.

Trust is also not synonymous with satisfaction. Satisfaction primarily reflects an evaluation of a past experience, while trust relates to expectations about the system's and the business's behavior in current and future interactions. Customers may be satisfied with the system's processing speed but still distrust how the system collects and uses their data.

2.5. Trust as a mediating mechanism between AI risk and experiential value

Studies on digital transactions show that trust and perceived risk are two closely related constructs that simultaneously influence customer decisions and behavior (Pavlou, 2003; Kim et al., 2008). In the context of AI, trust also directs the extent to which users are willing to rely on a system they cannot fully understand or control (Lee & See, 2004; Glikson & Woolley, 2020). Research on customer experience with AI also shows that trust plays a significant mediating role in conveying the impact of service quality, convenience, and personalization on customer experience (Ameen et al., 2021). Based on this, this study proposes trust as a theoretical mediating mechanism, rather than a moderating mechanism, in the relationship between AI-related risk and experiential value.

A moderating specification would imply that trust changes the strength or direction of the direct relationship between AI-related risk and experiential value. That is not the mechanism proposed here. In premium services, where financial and symbolic investment heightens vulnerability, the framework specifies a transmission sequence: perceived AI-related risk first erodes trust in the AI system and/or the service provider, and this erosion subsequently reduces experiential value. Trust is therefore positioned as a mediator; moderation remains a possible boundary condition for future empirical testing rather than an asserted relationship in this review.

Firstly, perceived AI risks can erode trust. When customers perceive algorithms to be opaque, data potentially misused, choices limited, or interactions dehumanized, they have less basis to expect that the system and the service provider will protect their interests. The relationship between perceived risk and trust has been documented in studies of online transactions and decision-making in technological environments (Pavlou, 2003; Kim et al., 2008).

Secondly, trust can contribute to maintaining or enhancing the value of the experience. Trust helps customers accept vulnerability, reduces psychological costs, and makes them willing to rely on technology in

complex or uncertain situations (Mayer et al., 1995; Lee & See, 2004). In AI-powered services, trust also helps customers focus on the benefits of convenience, personalization, and service quality, thereby improving how they evaluate the experience (Ameen et al., 2021). Without trust, customers must spend more time and effort monitoring the system, scrutinizing decisions, or searching for alternatives; these costs can diminish the value of the experience even if functional outcomes remain assured.

Thirdly, AI risks can indirectly impact the value of the experience through changes in trust. The proposed theoretical relationship chain is: Increased AI-related risk -> Decreased trust -> Reduced experiential value.

This mechanism may operate throughout the entire customer journey. Trust influences the willingness to provide data and use AI-powered services before the experience, how customers interpret AI activity during the experience, and their overall evaluation after the experience. However, previous studies have only provided evidence for individual component relationships and have not fully tested the intermediate chain in the context of premium services. Therefore, this is a theoretical mechanism proposed by the study and does not rule out the possibility that AI risk also directly impacts experiential value.

2.6. The integrated logic of the theoretical framework

From the perspective of conservation of resources (COR) theory, AI integration could threaten resources that customers value in premium services, including privacy, autonomy, certainty, and a sense of recognition (Hobfoll, 1989; Hobfoll et al., 2018). These threats constitute perceived risk and can erode trust in AI systems as well as the service providers (Pavlou, 2003; Kim et al., 2008; Glikson & Woolley, 2020). This erosion of trust can then affect how customers value the functional, emotional, relational, and symbolic aspects of the experience (Ameen et al., 2021). Based on a synthesis of these arguments, the study proposes trust as a mediating mechanism connecting AI risk with experiential value throughout the customer journey (Lemon & Verhoef, 2016).

3. Methodology: bibliometric review

3.1. Literature review process and search strategy

The study performed a systematic bibliometric analysis based on the guidelines of Donthu et al. (2021) and the modified PRISMA of Page et al. (2021). Data was collected from Web of Science on June 20, 2026. The search was conducted in the Topic Search (TS) field, including title, abstract, author keywords, and Keywords Plus. The search sequence combined three groups of terms: (i) AI technology; (ii) experience, interaction, and service context; and (iii) risk, trust, privacy, transparency, and related negative consequences. The identification search was limited to English-language records, article type, and the period 2015–2026. The query string was: TS=("artificial intelligence" OR "generative artificial intelligence" OR "generative AI" OR "machine learning" OR chatbot* OR "service robot*" OR "algorithmic decision*" OR "intelligent service system*") AND TS=("customer experience" OR "consumer experience" OR "service experience" OR "service encounter*" OR "customer journey" OR hospitality OR tourism OR hotel*) AND TS = (risk* OR "perceived risk" OR trust OR privacy OR vulnerab* OR transparen* OR explainab* OR control OR dehuman* OR bias OR fairness OR ethic* OR failure*) AND PY=(2015-2026) AND LA=(English) AND DT=(Article).

To avoid ambiguity, the study distinguishes the identification window from the analytical window. The initial query covered 2015–2026 to identify the broader body of potentially relevant work. Before deduplication

and topical screening, 54 records published before 2021 were excluded. Consequently, every dataset-based bibliometric indicator and map reported in this article refers to the final analytical corpus of 390 publications from 2021 to June 20, 2026; 2015–2026 denotes only the initial identification window.

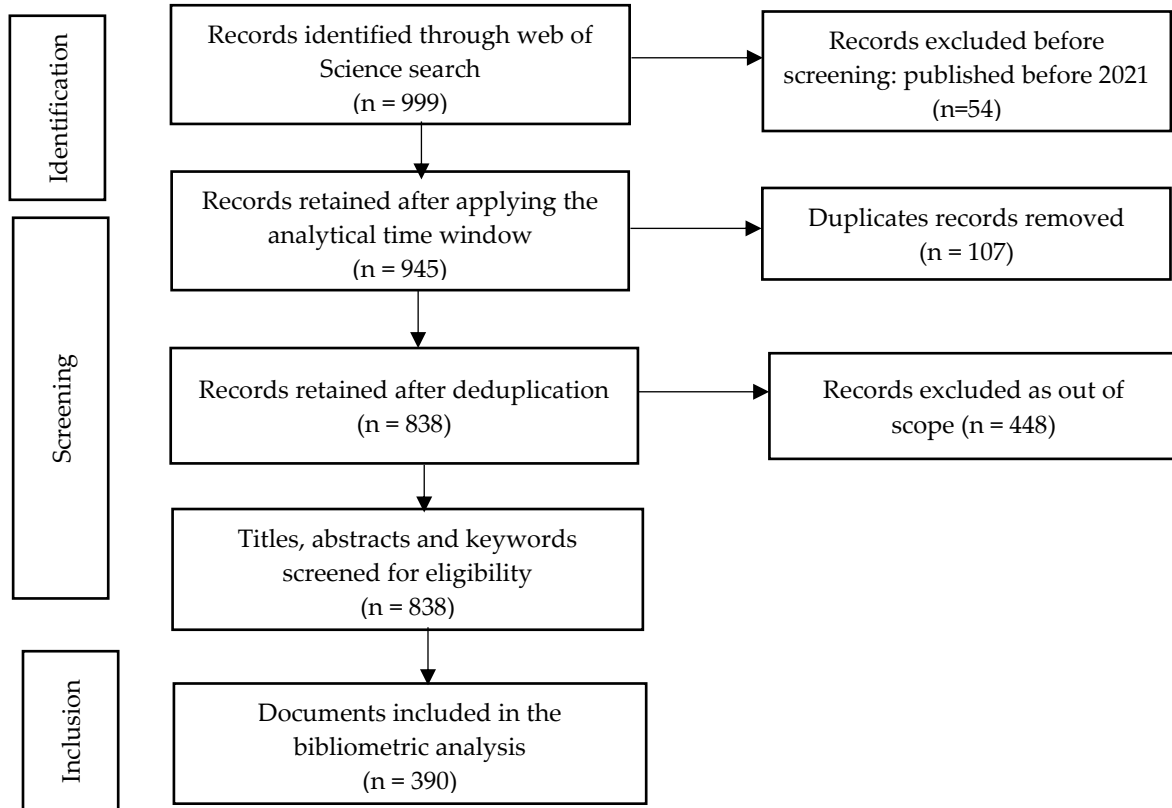


Figure 1. PRISMA-adapted identification, screening, and inclusion process

Source: Authors' adaptation from Page et al. (2021)

The initial search yielded 999 records. Although the initial query covered the period 2015–2026 to fully identify relevant publications, the analysis set was limited to the period 2021–2026. Accordingly, 54 records published before 2021 were excluded, leaving 945 records. The data were further normalized by DOI and title; 107 duplicate records were excluded, leaving 838 documents. The titles, abstracts, and keywords of these documents were screened according to their relevance to AI, customer interaction, and service experience. A total of 448 documents outside the scope of the study were excluded. The final dataset comprises 390 documents published from 2021 to June 20, 2026, which were used consistently for bibliometric analyses using Bibliometrix/Biblioshiny.

3.2. Screening criteria, research dataset, and academic characteristics of the study sample

Following the identification and screening process shown in Figure 1, documents were retained that met the following conditions: indexed in the Web of Science; published from 2021 to June 20, 2026; scientific paper type; and directly related to AI in tourism, hospitality, or service experiences. Studies that were purely technical, medical-clinical, or did not consider customer interaction, behavior, and evaluation were excluded from the dataset. The screening results formed the final dataset of 390 documents, which were used consistently for subsequent analyses.

Table 1 shows a dataset of 390 documents from 46 sources published from 2021 to June 20, 2026. The annual growth rate is 16.27%, and the average age of the documents is 1.77 years, reflecting the up-to-date nature and rapid expansion of the field. Each document receives an average of 34.4 citations; however, this figure may be influenced by the high number of citations and may not be consistent with research quality. Since the 2026 data is incomplete, the growth rate is only descriptive.

Table 1. Descriptive statistics of the research dataset

No.	Description	Results
A.	Core dataset information	
1.	Analytical time span	2021–June 20, 2026
2.	Sources (journals)	46
3.	Documents	390
4.	Annual Growth Rate (%)	16.27
5.	Average Age of Documents	1.77
6.	Average Citations Per Document	34.4
7.	Total cited references	20,454
B.	Document content	
8.	Keyword Plus (ID)	792
9.	Author Keywords (DE)	1,569
C	Authors	
10.	Total authors	1,155
11.	Authors of single-authored articles	21
D	Author collaborations	
12.	Single-authored articles	22
13.	Average co-authors per article	3.68
14.	International co-authorship (%)	47.69
E	Document types	
15.	Regular articles	350
16.	Article, data paper	1
17.	Early-access articles	39

Source: Authors’ analysis using Biblioshiny, based on Aria and Cuccurullo (2017)

Data retrieval date: 20/06/2026

The dataset contains 792 Keywords Plus and 1,569 author keywords, indicating a diverse range of topics and providing a basis for keyword co-occurrence analysis. Collaboration is relatively high, with an average of 3.68 co-authors per article and an international collaboration rate of 47.69%. In terms of type, the dataset mainly consists of 350 regular articles and 39 early-access articles, suitable for analyzing knowledge structure and further research topics.

Table 2 shows that the number of publications increased from 24 articles in 2021 to 160 articles in 2025, with a particularly strong increase in the period 2024–2025. 51 articles were recorded in 2026 at the time of retrieval; since the data does not cover the entire year, this number cannot be interpreted as a sign of declining publications.

Table 2. Number of publications and average annual citations in research on AI and service experience

Year	MeanTCperArt (average citations per article)	N (number of articles)	MeanTCperYear (average citations per year)	CitableYears (number of years that can be cited)
2021	120.33	24	20.06	6
2022	84.42	31	16.88	5
2023	47.54	39	11.88	4
2024	38.78	85	12.93	3
2025	14.98	160	7.49	2
2026	7.16	51	7.16	1

Source: Authors’ analysis using Biblioshiny, based on Aria and Cuccurullo (2017)

The average citations per article decreased from 120.33 in 2021 to 7.16 in 2026, mainly due to newer works having shorter citation accumulation periods. The average annual citation index partially adjusts for this difference, but may still be influenced by some highly cited articles. Overall, the results reflect the rapid expansion of research on AI and service experiences, and highlight the need for cautious interpretation of recent years' indicators.

4. Results and concept synthesis

4.1. Results of bibliometric analysis

4.1.1. Knowledge structure: keyword co-occurrence network

Figure 2 presents the keyword co-occurrence network in 390 documents from the research dataset. In the network, the size of the node reflects the frequency of keyword occurrence; the thickness of the link indicates the degree to which two keywords appear together; and the distance between nodes indicates the degree of content proximity. The results show that the knowledge structure of the domain is organized into four relatively closely related thematic clusters.

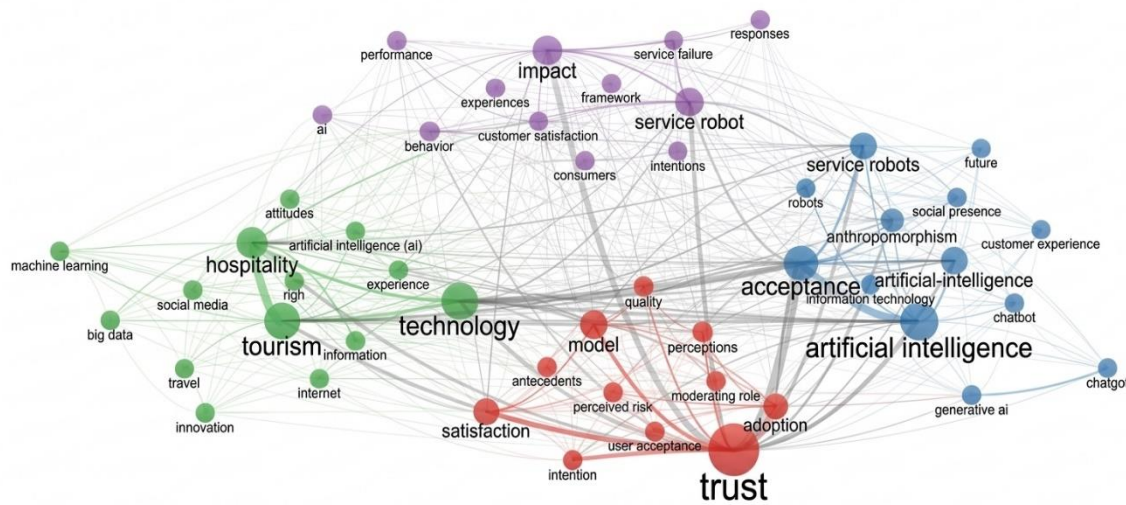


Figure 2. Keyword co-occurrence network in AI and service-experience research

Note: Only selected representative labels are displayed to improve readability; node positions, links, and cluster assignments are unchanged.

Source: Authors' analysis of Web of Science data using Biblioshiny, based on Aria and Cuccurullo (2017)

The first cluster, shown in red, centers around the keyword *trust*, connecting with *adoption*, *model*, *satisfaction*, *intention*, *perceptions*, and terms related to technology acceptance behavior. In this cluster, *trust* has a large node size and is located in the center of the entire network, indicating that *trust* is one of the most important concepts in AI research and service experience. The location of *trust* at the intersection of clusters also suggests that this concept is often studied concurrently with AI acceptance, customer evaluation, and experience outcomes. However, the co-occurrence of keywords only reflects the relationship within the knowledge structure and is not yet empirical evidence for the mediating role of *trust*.

The second cluster, shown in blue, is formed around the keywords *artificial intelligence*, *acceptance*, *service robots*, *anthropomorphism*, *social presence*, *customer experience*, *chatbot*, and *generative AI*. This cluster reflects the research trend on AI applications at service touchpoints and customer responses to these technologies. The simultaneous presence of *service robots*, *anthropomorphism*, and *social presence* indicates that research is not only interested in AI's functional capabilities but also in how human characteristics influence customer perception and acceptance. The terms “*chatbot*” and “*generative AI*” are smaller in scope, reflecting relatively new research directions within the dataset.

The third cluster, shown in green, focuses on *technology*, *tourism*, *hospitality*, *machine learning*, *big data*, *the internet*, *social media*, and *innovation*. This forms the foundational context of the field, reflecting the application of digital technology and AI in tourism and hospitality. Within this cluster, *technology*, *tourism*, and *hospitality* are large-scale and interconnected with many other clusters, indicating that AI research in services is primarily developed from issues related to digital transformation, innovation, and the application of technology in tourism and hospitality operations.

The fourth cluster, shown in purple, is organized around the keywords *impact*, *service robot*, *performance*, *experience*, *service failure*, *responses*, and terms related to interaction outcomes. This cluster focuses on the impact of robots and AI on service efficiency, emotional responses, satisfaction, and customer

experience. The inclusion of service failure indicates that research has begun to shift from emphasizing the benefits of technology to considering the problems that arise when AI or robots fail to meet customer expectations.

The clusters do not exist independently but are connected through central keywords such as trust, artificial intelligence, acceptance, technology, service robot, and impact. This interconnected structure shows that three main research directions are intersecting: the application of AI technology; customer acceptance and trust; and the consequences for experience, satisfaction, and service efficiency. Trust emerges as a crucial link between technological characteristics and customer responses, while tourism and hospitality is the prominent application context of the entire network.

Notably, keywords directly reflecting the downsides of AI, such as perceived risk, privacy, service failure, or negative reactions, are smaller in scale compared to artificial intelligence, acceptance, technology, and trust. This result suggests that the current knowledge structure still leans towards the application and acceptance of technology, while risk mechanisms related to loss of control, privacy, lack of transparency, and dehumanization have not yet formed a central research focus. This is a crucial gap for further research to synthesize risk mechanisms and develop a conceptual framework connecting AI risk, trust, and experiential value.

Overall, Figure 2 shows that research on AI in service experience has formed a multi-clustered but highly interconnected knowledge structure. The analysis results support the view that trust is a crucial connecting concept in the field. However, the mediating role of trust between AI risk and experiential value is a theoretical relationship proposed from conceptual synthesis and needs to be tested by empirical research; it cannot be asserted solely from keyword co-occurrence networks.

4.1.2. Thematic structure and research scope

Figure 3 presents a topic map based on the centrality and density of keyword clusters. Centrality reflects the topic's connectivity to the entire domain, while density represents the level of development and internal cohesion. Accordingly, topics are divided into four groups: dynamic, foundational, specialized, and emerging or declining (Aria & Cuccurullo, 2017).

The trust–adoption–intention cluster falls within the dynamic topic region, indicating that trust, acceptance, and intention to use have both a relatively developed structure and broad connections with other research directions. This result confirms the prominent position of trust in the knowledge structure of AI and service experience but is not direct evidence of trust's mediating role. The cluster of impact–service robot–satisfaction lies near the boundary between the themes of motivation and platform, reflecting growing interest in the impact of service robots on satisfaction and experience outcomes.

The artificial intelligence–acceptance–generative AI cluster is located near the central axis and has a relatively high density, representing a combination of the developed research stream on AI acceptance and the newer research direction on generative AI. Meanwhile, the tourism–technology–hospitality cluster belongs to the foundation topic group, with high centrality but low density. This shows that tourism and hospitality is an important application context, connecting many research directions but has not yet formed a separate in-depth structure on AI risks.

The two clusters, artificial-intelligence–perceptions–personalization and service robots–anthropomorphism–experience, are in the emerging or declining topic area, with low centrality and density.

The map is not enough to determine whether these are emerging or declining themes; however, in the context of the recent increase in publications, it can be cautiously interpreted that these are emerging directions but not yet fully connected to the general intellectual structure. These clusters reflect interest in personalization, customer perception, robot humanization, and interactive experiences, which are issues that have direct implications for premium service.

The value co-creation–roles cluster belongs to a specialized thematic group, with high density but low centralization. The results show that research on the roles of actors in value co-creation has developed relatively tightly within the cluster but has little connection to the main research streams on AI, trust, and service experience.

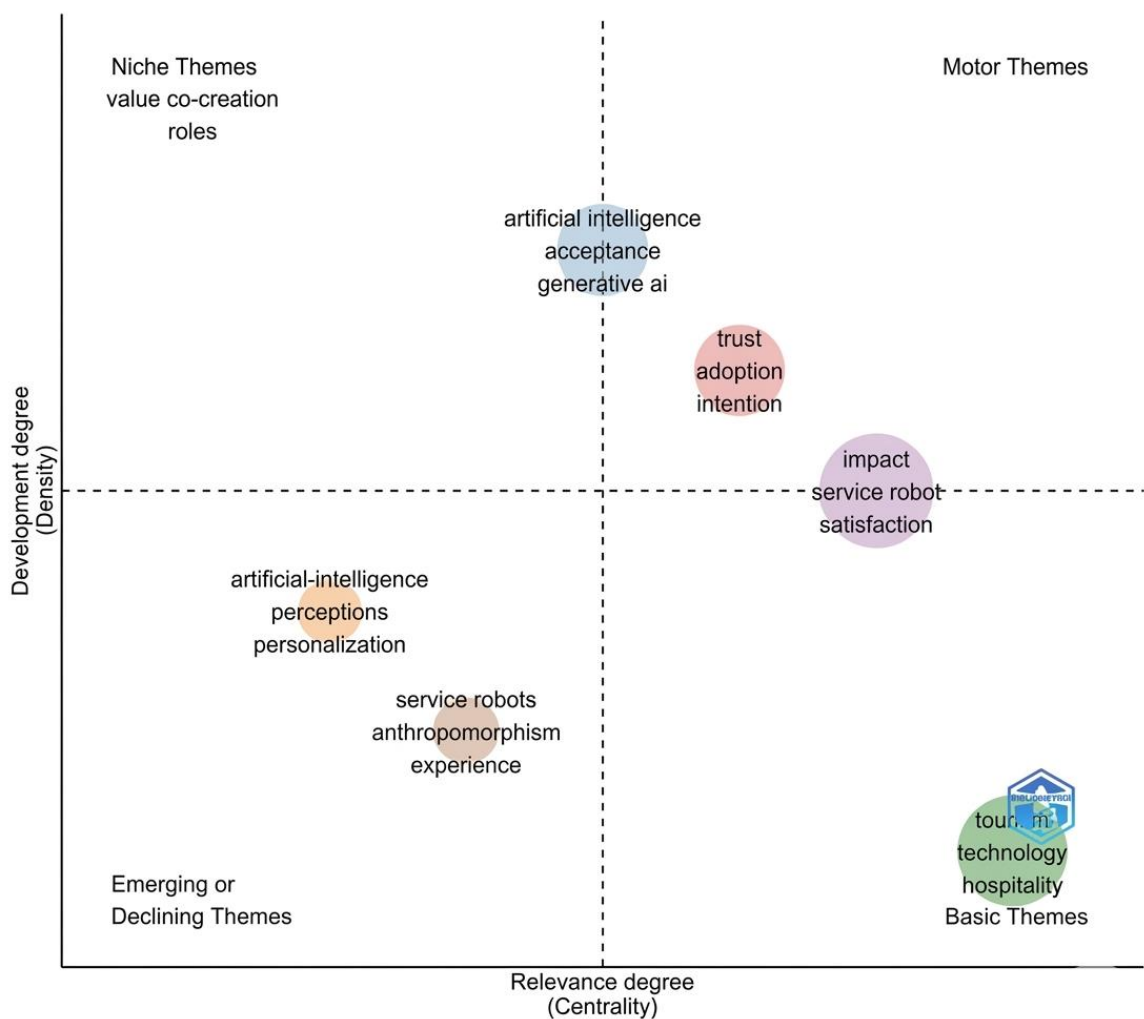


Figure 3. Research topic map on AI and service experience

Source: Authors’ analysis of Web of Science data using Biblioshiny, based on Aria and Cuccurullo (2017)

Overall, the field is currently driven by research on AI trust and acceptance, the impact of service robots, and the application of technology in tourism and hospitality. Conversely, lack of transparency, privacy, diminished control, and dehumanization have not formed independent thematic clusters. This gap provides the basis for further synthesis on AI risk mechanisms and their relationship to trust and experiential value.

Table 3 shows the research structure on AI and service experience, formed from seven thematic clusters with varying levels of development. The Trust–Adoption–Intention cluster holds a dynamic position, indicating that trust and acceptance of technology are prominent research directions in the field. The Impact–Service Robot–Satisfaction and Tourism–Technology–Hospitality clusters reflect the application of AI in tourism and hospitality and the impact of service robots on experience outcomes.

Table 3. Research topic clusters on AI and service experience

Topic cluster	Identifying keywords on the map	Location and level of development	Research focus and implications for premium services
Trust–Adoption–Intention	trust, adoption, intention	Dynamic theme; relatively high centrality and density	Focus on trust, acceptance, and intention to use AI. The prominent position shows that trust is a crucial connecting concept, but does not directly demonstrate its mediating role.
AI–Acceptance–Generative AI	artificial intelligence, acceptance, generative AI	Transition zone near the central axis; relatively high density	Reflects the expansion from AI acceptance research to generative AI. High-end services need to simultaneously consider authenticity, transparency, and accountability when deploying new AI tools.
Impact–Service Robot–Satisfaction	impact, service robot, satisfaction	Near the boundary between dynamic and foundational themes	Consider the impact of service robots on satisfaction and experience outcomes. The theory of human-robot interaction and experience recovery when technology fails to meet expectations needs to be developed.
Tourism–Technology–Hospitality	tourism, technology, hospitality	Foundational theme; high centrality but low density	Formulates the main application context of AI in tourism and hospitality. Theoretical frameworks suitable for the privacy, personalization, and human interaction of high-end services need to be developed.
AI Perceptions–Personalization	artificial-intelligence, perceptions, personalization	Emerging or declining theme; centrality and low density	Focus on customer perception and personalization through AI. A prominent implication is the trade-off between personalization, privacy, and customer control.
Service Robots–Anthropomorphism–Experience	service robots, anthropomorphism, experience	Emerging or declining theme; limited connectivity	Reflects the role of robot humanization and interactive experiences. In premium services, consideration should be given to social presence, emotional responsiveness, and the ability to maintain a sense of being cared for.
Value Co-creation–Roles	value co-creation, roles	Specialized theme; high density but low centrality	Emphasis should be placed on the customer's role in co-creating value with businesses and technology. This research direction needs to be more clearly connected to empowerment, trust, and experiential value.

Source: Authors' synthesis of the keyword co-occurrence analysis and thematic-map results in Figures 2 and 3, using Web of Science data and Biblioshiny, based on Aria and Cuccurullo (2017)

Meanwhile, personalization, humanization of robots, and co-creation of value remain in transitional, peripheral, or specialized positions. Notably, issues directly related to lack of transparency, privacy, diminished control, and dehumanization have not yet formed independent thematic clusters. This result

suggests that current research still focuses more on the application and acceptance of AI, providing a basis for synthesizing risk mechanisms and proposing trust as a mediating mechanism that needs to be tested in subsequent studies.

Figure 4 shows that the research is primarily concentrated in specialized journals on tourism, hospitality, and service technology. The International Journal of Hospitality Management leads with 53 articles, followed by the International Journal of Contemporary Hospitality Management with 36 articles and Current Issues in Tourism with 26 articles. The Journal of Hospitality and Tourism Technology and Sustainability each have 24 articles.

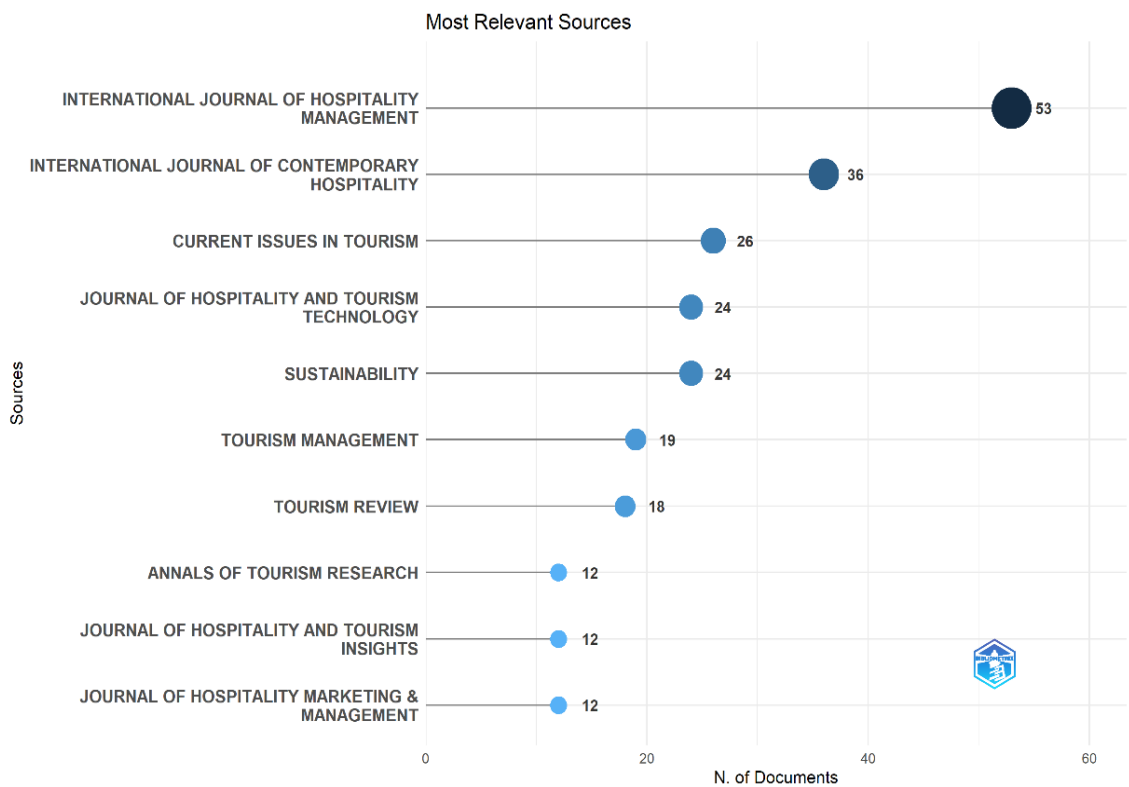


Figure 4. Most published sources in the research dataset

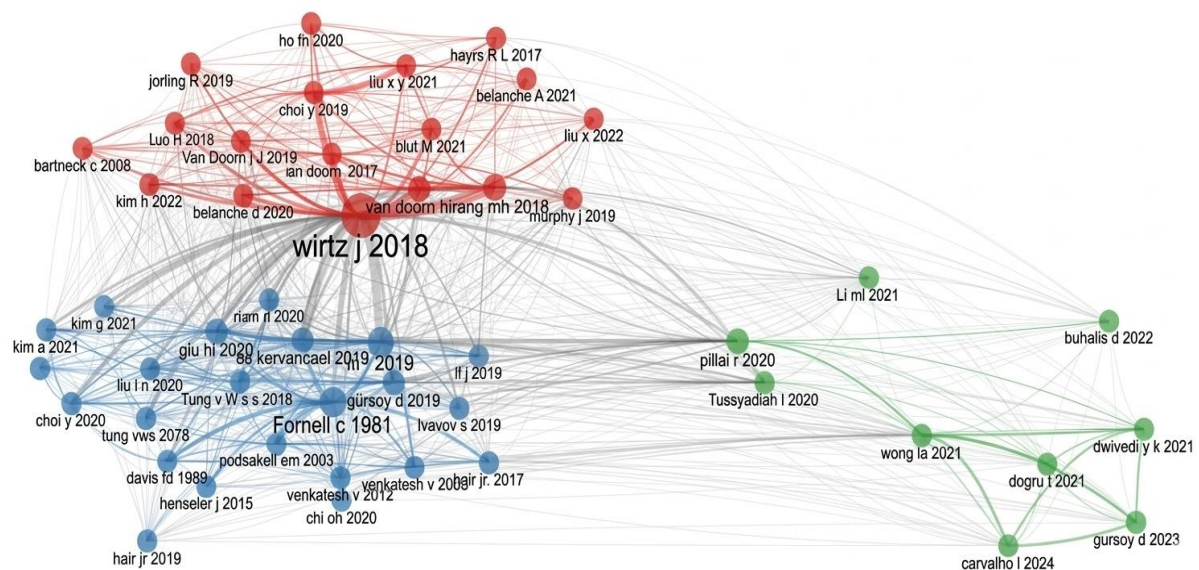
Source: Authors analyzed Web of Science data using Biblioshiny, based on Aria and Cuccurullo (2017)

The top ten sources contributed 236 out of 390 documents, equivalent to 60.51% of the dataset. The results show that the field has a relatively high concentration of publications and is mainly developed in tourism and hospitality research. The presence of Tourism Management, Annals of Tourism Research, and journals specializing in hospitality technology also reflects the interdisciplinary nature between service management, customer behavior, and AI applications. However, the number of publications only reflects the productivity of the source, not directly the level of academic influence.

4.1.3. Publication sources and knowledge base structure

Figure 5 illustrates the co-citation network among influential literature in the field, formed from three main clusters. The red cluster centers around Wirtz et al. (2018), reflecting research on service robots, automation, and technology interaction in services. The blue cluster, with Fornell et al. (1981) holding a

The dense links between the three clusters show that AI research in service experiences is developed on a combination of service science, consumer behavior, and tourism technology. Wirtz et al. (2018) is centrally located, acting as a connector between foundational research and new directions in AI and service robots. However, the co-citation network only reflects the influence structure and academic relationships between the documents, and does not represent international collaboration.



Note: Labels are limited to representative documents for legibility; node positions, links, and cluster assignments are unchanged.

4.2.1. From technological risk to perceived risk related to AI

According to the conservation of resources (COR) theory, risk arises when customers perceive that resources they value, such as privacy, autonomy, certainty, psychological security, and a sense of recognition, are at risk of being threatened or diminished (Hobfoll, 1989, 2001; Hobfoll et al., 2018). In premium services, these resources are particularly important because customers not only expect functional efficiency but also

value discretion, exclusivity, and quality of interaction. Therefore, AI risk should be viewed as a cognitive-emotional phenomenon that can develop and accumulate throughout the customer experience journey, rather than simply a consequence of technical failure.

4.2.2. Core mechanisms creating AI risk in premium service experiences

Based on this, the results of the bibliometric analysis combined with theoretical synthesis identify four core mechanisms that create AI risk in premium service experiences. From the perspective of conservation of resources (COR) theory, the four core mechanisms forming AI risk in premium service experiences are identified as follows.

Lack of algorithmic transparency. AI often operates according to “black box” logic, making it difficult for customers to understand how data is used or why a particular decision, proposal, or service allocation is made (Burrell, 2016; Pasquale, 2015). In premium services, this lack of transparency can lead customers to doubt the fairness of decisions related to personalization, upgrades, or incentives. According to COR, the inability to predict and explain system performance threatens certainty, a sense of fairness, and psychological security, thereby creating perceived risk even when service outcomes remain positive.

Data asymmetry and privacy concerns. Businesses and AI systems have the ability to collect, connect, and process personal data at levels beyond the customer's observation or control (Acquisti et al., 2015; Martin, 2018). This asymmetry increases feelings of vulnerability, especially when customers are unaware of how their data is being used or with whom it is being shared. In premium services, where discretion and security are crucial components of the experience, the risk of privacy loss directly threatens customer control over data, their sense of security, and their perceived vulnerability.

Reduced control and algorithmic dependence. As AI automates recommendation, allocation, and personalization of services, the power of choice may gradually shift from the customer to the system. Customers may feel manipulated, lacking alternatives, or finding it difficult to request staff intervention. Simultaneously, recommendations based on past data risk “framing” the experience and limiting future choices (Longoni et al., 2019; Castelo et al., 2019; Huang & Rust, 2021). According to COR, this dependence threatens autonomy, decision-making capacity, and control-resources particularly crucial in high-end services where customers expect flexibility, uniqueness, and responsiveness to individual needs.

Dehumanization of the experience. AI may replace or mediate human interaction at emotionally and relational touchpoints. While technology can improve speed and consistency, reducing staff presence can leave customers feeling underempathized, unacknowledged, or uncared for as individuals (Huang & Rust, 2018; Mende et al., 2019). In high-end service, dehumanization threatens relational and emotional resources, including social connection, recognition, dignity, and a sense of being valued. Therefore, the experience may still be negatively evaluated even if the functional effectiveness of AI is assured.

The four mechanisms above are not entirely independent but can interact at the same touchpoint. For example, a lack of transparency can increase feelings of loss of control, while data asymmetry can erode trust and amplify feelings of dehumanization. Table 4 summarizes the content, manifestations, and resources at risk corresponding to each mechanism in the context of premium services.

Table 4 shows that AI risk mechanisms do not exist independently but can interact and accumulate across multiple touchpoints in the customer journey. From the perspective of conservation of resources (COR) theory, the lack of transparency and data asymmetry can increase the feeling of loss of control, while the decline in human interaction continues to threaten relational and emotional resources. Therefore, risk

accumulation along the journey is considered a characteristic process, not an independent mechanism. This approach provides a basis for the research to propose that trust is the mediating mechanism conveying the impact of AI risk on experiential value.

Table 4. Mechanisms creating perceived AI risk in premium service experiences

AI risk mechanism	Mechanism description	Manifestation in premium service experiences	Resources at risk according to COR	Typical references
Algorithmic opacity	Customers cannot understand or explain how AI uses data to make decisions or recommend services.	Difficulty in explaining why services, upgrades, or special offers are recommended or not recommended; doubts arise regarding the fairness and accountability of the system.	Predictability, certainty, a sense of fairness, and psychological security.	Burrell (2016); Pasquale (2015)
Data asymmetry and privacy concerns	Businesses and AI systems have the ability to collect, connect, and process personal data beyond what customers can observe or control.	Concerns about being tracked, data misused, or privacy violated; a diminished sense of privacy and security expected in premium services.	Privacy, data control, safety, and a state of vulnerability.	Acquisti et al. (2015); Martin (2018); Hu & Min (2023)
Loss of control and algorithmic dependence	The power of service selection and decision-making is gradually shifting from customers to AI systems; recommendations based on past data may limit future choices.	The experience feels overly manipulated, lacking alternatives, and difficult to request staff intervention; the experience risks becoming standardized, reducing flexibility, surprise, and uniqueness.	Autonomy, decision-making capacity, control, and flexibility of experience.	Longoni et al. (2019); Castelo et al. (2019); Huang & Rust (2021)
Dehumanization	AI replaces or mediates human interaction at emotionally and relational touchpoints.	A lack of empathy reduces the feeling of being recognized, respected, and cared for as an individual; the experience becomes standardized despite improved functional efficiency.	Social connection, recognition, dignity, emotional security, and a sense of belonging.	Huang & Rust (2018); Mende et al. (2019)

Source: Authors' synthesis of the Web of Science analytical corpus (2021–June 20, 2026) and related theoretical literature.

4.2.3. The accumulation of AI risk along the customer journey: interpretation in the context of luxury hotels

In luxury hotels, the service experience is constructed through a series of touchpoints before, during, and after the stay (Lemon & Verhoef, 2016). When AI is integrated into these touchpoints, risk does not appear at a single point in time but accumulates along the experience journey. At the initial touchpoints, AI often creates perceived risk related to lack of transparency and data asymmetry, undermining the initial sense of fairness and trust of luxury customers (Pasquale, 2015; Hu & Min, 2023). In the emotionally charged touchpoints during the stay, risk shifts to feelings of loss of control and dehumanization when human

interactions are mediated by technology (Huang & Rust, 2018; Mende et al., 2019). In the later stages of the experience, the personalization logic based on past data can “frame” the experience, diminishing the sense of uniqueness – a core element of premium service (Castelo et al., 2019; Huang & Rust, 2021).

More importantly, these risks do not exist independently but resonate over time, forming dynamic perceived risk throughout the experience journey (Mitchell, 1999). This shows that AI risk is a challenge in overall experience management; based on a synthesis of theory, research proposes that trust is the mediating mechanism that helps convey the impact of AI risk on experiential value throughout the customer journey.

4.3. Trust as a proposed mediating mechanism in AI-Powered premium service experiences

The results in Figures 2 and 3 show that trust is a prominent concept in the knowledge structure of AI and service experiences. However, the bibliometric analysis only reflects the level of interest and academic association of this concept, not directly proving its mediating role. That role is proposed based on a synthesis of bibliometric results and theory.

Four mechanisms in Table 4 can undermine trust in AI systems and service providers. When customers do not understand how algorithms make decisions, are concerned about data being used unexpectedly, feel their choices are limited, or perceive interactions as becoming dehumanizing, they have less basis to expect that the system and the business will protect their interests (Pavlou, 2003; Kim et al., 2008). In the context of AI, trust is also influenced by the capabilities, predictability, transparency of the system, and how businesses deploy and monitor the technology (Lee & See, 2004; Glikson & Woolley, 2020).

Trust also affects how customers evaluate the value of the experience. When they believe that AI operates competently and is responsibly managed by the business, customers may accept a certain degree of uncertainty and pay more attention to the benefits of the technology. Conversely, a decline in trust increases the psychological cost, time, and effort required to monitor the system or seek support, which can reduce the value of the experience (Mayer et al., 1995; Ameen et al., 2021).

Therefore, the study proposes a chain of relationships: increased AI-related risks → decreased trust → decreased experiential value. This mechanism can be formed and updated through touchpoints before, during, and after service (Lemon & Verhoef, 2016). This is a theoretical proposal that needs to be tested with empirical data.

4.4. Experiential value under the impact of AI in premium services

The overall results show that the impact of AI on experiential value is multifaceted. AI can increase functional value through accuracy, convenience, responsiveness, and personalization. However, the risk mechanisms presented in Table 4 can simultaneously degrade emotional, relational, symbolic, and controllable value. Therefore, improving technical efficiency does not guarantee that AI will create positive experiential value (Holbrook, 1999; Huang & Rust, 2018).

This trade-off is particularly evident in premium services, where customers not only expect accurate results but also value discretion, choice, uniqueness, and a feeling of being cared for as an individual. An AI-powered touchpoint might be highly valued for its speed, but its overall value is diminished if customers feel over-monitored, overly manipulated, or unable to access staff support. Experiential value is therefore shaped by how customers simultaneously assess the benefits of AI and the resources at risk of degradation throughout the entire service journey (Lemon & Verhoef, 2016).

In this process, trust is proposed as the mechanism linking AI risks to experiential value. When trust is maintained, customers may accept a degree of uncertainty and continue to recognize the benefits of AI; when trust declines, the resulting psychological and relational costs can diminish experiential value even if the system remains effective (Ameen et al., 2021).

4.5. Synthesis and proposal of a conceptual framework

The results of the bibliometric analysis and theoretical synthesis show that AI risk in premium services is shaped by how customers interpret the impact of technology on the resources they value. In a context where customers expect discretion, choice, exclusivity, and quality of interaction, the same AI application can create functional value but can also degrade emotional, relational, or symbolic value.

Based on the COR and customer journey approach, the study integrates the four risk mechanisms identified in Table 4 with the argument on trust in section 4.3. The proposed framework views trust as the theoretical mediating mechanism through which AI-related risk can influence how customers evaluate the value of the experience throughout the entire service journey.

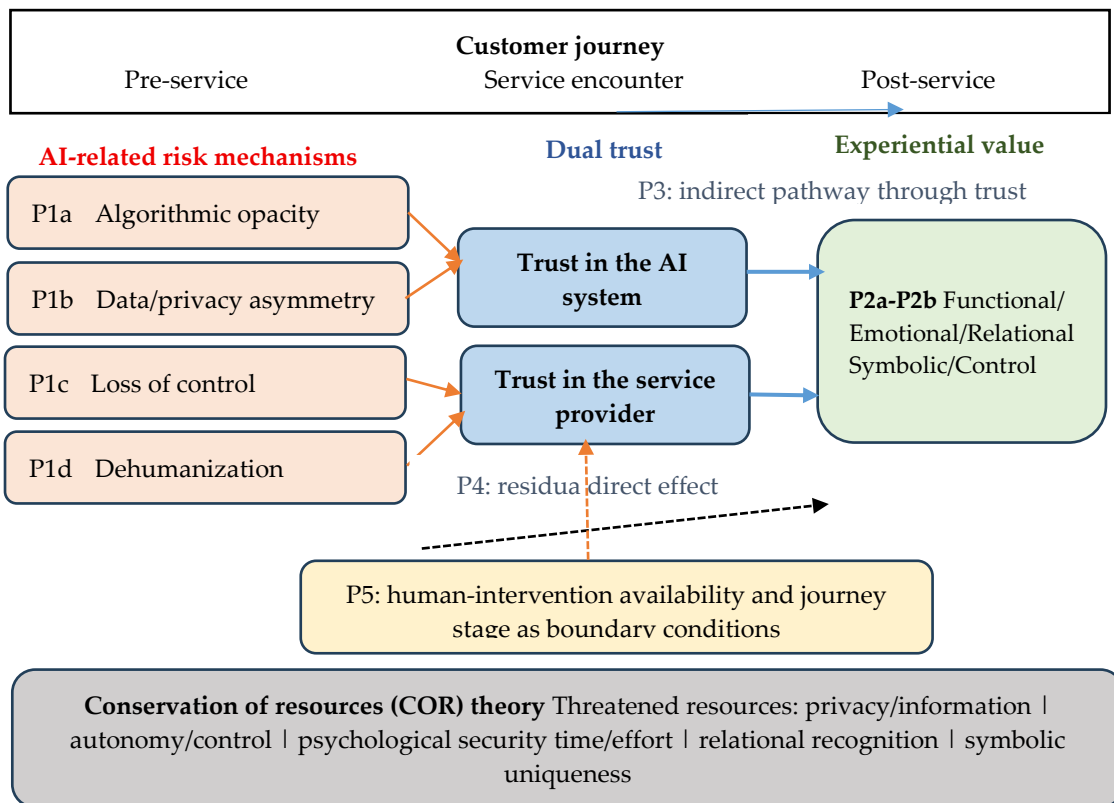


Figure 6. Integrated conceptual framework of AI-related risk, dual trust, and experiential value

Source: Authors' development from COR theory and the customer-journey perspective

Figure 6 focuses on illustrating the proposed indirect impact curve: increased AI-related risks can erode trust, thereby reducing experiential value. According to COR, these risks are linked to perceptions of the risk of decreased privacy, autonomy, psychological safety, and a sense of recognition (Hobfoll, 1989; Hobfoll et al., 2018). This framework is a theoretical proposal; other direct or indirect relationships need to be tested in further research. The arrows in Figure 6 represent theoretically proposed paths that require empirical testing; they are not causal estimates derived from the bibliometric analysis.

5. Discussion, Implications, and Future Research

5.1. Key research gaps

The analysis reveals that research on AI and service experience still focuses primarily on trust, technology acceptance, service robots, and experience outcomes. The Trust–Adoption–Intention cluster holds a driving position, while Tourism–Technology–Hospitality forms the context of the field. Conversely, issues directly related to lack of transparency, privacy, loss of control, and dehumanization have not formed independent thematic clusters. This suggests that current research still focuses more on the application and acceptance of AI than on the process of perceived risk formation.

The theoretical synthesis identifies four risk mechanisms that are likely to interact and accumulate in the customer journey. From a COR perspective, these mechanisms create risk when they threaten resources that customers value, such as privacy, autonomy, psychological safety, and a sense of recognition. Trust is prominent in the knowledge structure, but the mediating role between AI risk and experiential value is only proposed at the theoretical level and has not been empirically tested.

The gap is particularly clear in high-end services, where customers have high expectations for privacy, exclusivity, and quality human interaction. Therefore, AI needs to be studied as an agent involved in shaping the entire customer journey, rather than simply evaluating the technology's effectiveness or intended use.

5.2. Theoretical implications

The research contributes in three ways. First, AI risk is reconceptualized as a process that threatens and degrades customer resources, rather than simply a consequence of technical errors. Second, combining COR with a customer journey approach helps explain how risks can form, interact, and accumulate across multiple touchpoints. Third, the research proposes that trust is the mediating mechanism conveying the impact of AI risk on experiential value. This proposal expands the role of trust from a result of technology acceptance to a psycho-relational mechanism that needs to be tested.

5.3. Management implications

High-end service businesses need to implement AI in a transparent manner, protecting data and maintaining customer choice. Customers need to be informed about the purpose of data collection, the principles behind recommendation formation, and the ability to request staff intervention. Emotional touchpoints should maintain appropriate human presence, rather than being completely automated.

Businesses also need to monitor trust throughout the customer journey and build recovery processes when AI makes inappropriate decisions. Therefore, AI evaluation should not be based solely on speed or accuracy but also on the ability to maintain control, a sense of security, and experiential value.

To operationalize these principles, managers should establish a stage-specific human-in-the-loop protocol. Before service, five-star hotels and priority-banking providers should disclose which data inform AI recommendations, provide meaningful consent and opt-out choices, and display a visible route to human advice. During service, emotionally charged or high-stakes touchpoints—such as complaints, upgrade or credit decisions, and identity or payment problems—should trigger a warm handoff to an empowered employee without requiring customers to repeat information.

After service, managers should record contested automated decisions, notify customers when corrections are made, and use these incidents in periodic audits of fairness, privacy, and service recovery. AI dashboards should therefore combine speed and accuracy with opt-out rates, human-handoff time,

unresolved AI-related complaints, perceived control, and trust. These safeguards convert the proposed framework into observable management practices while preserving the efficiency benefits of AI.

5.4. Limitations and future research directions

The study has several limitations. Data was collected only from the Web of Science during the period 2021–2026, with the 2026 data being incomplete. Bibliometric analysis reflects knowledge structures but does not provide evidence of causality. Additionally, the conceptual framework is extrapolated to premium services and has not been validated with empirical data.

Future research should examine the mediating role of trust using quantitative, qualitative, or hybrid designs; track the variation of risk and trust throughout the customer journey; compare across cultures, service types, and AI application forms; and consider the differences between fully automated touchpoints and those combining AI with human intervention.

5. Conclusion

This study systematizes the knowledge structure of AI and service experience based on 390 publications from Web of Science between 2021 and 2026. The results show that trust and acceptance are prominent themes, while risk mechanisms remain scattered and have not yet formed independent research clusters. Theoretical synthesis identifies four risk mechanisms: algorithmic lack of transparency, data and privacy asymmetry, diminished control, and dehumanization of the experience.

Based on the COR framework and a customer journey approach, the study proposes that trust is the mediating mechanism conveying the impact of AI risk on experiential value. This framework is theoretically proposed, providing a foundation for empirical research and for designing customer-centric AI in premium services.

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