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# Biosignal-adaptive platforms

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**Abstract**

Personalization is a well-established concept that leverages a wide range of user data to tailor digital platforms to target audiences. Advances in sensor technologies now allow continuous recording of human activities, such as eye gaze, heartbeat, or facial muscle movements. The resulting biosignals can be processed and interpreted in real time using, for example, artificial intelligence methods, enabling closed-loop adaptation and deeper individualized personalization. We conceptualize such systems as biosignal-adaptive platforms (BAPs). Despite their potential, research on BAPs in electronic markets remains limited. This paper addresses this gap through three key contributions: (i) we develop a morphological box that captures the technical and functional complexity of BAPs and illustrates potential solution spaces; (ii) we conduct a systematic literature review and map existing studies onto this framework, highlighting configurations currently examined in e-commerce, auctions, and streaming services; and (iii) we identify technical, methodological, ethical, and societal challenges, providing guidance for responsible, human-centered design. Together, these contributions provide an understanding of BAP's capabilities and a foundation for future research and practice in electronic markets.

**Keywords** Biosignals · Personalization · Adaptive systems · Digital platforms · NeuroIS · Design

**JEL Classification** M15 · O30

## Introduction

Personalization is a well-established concept that enables the tailored delivery of products, services, and content to target audiences (Fan & Poole, 2006). These offerings are no longer merely tailored to collective user segments — the "us" — but are increasingly personalized to the individual — the "me" (Kaptein & Parvinen, 2015). Today, businesses increasingly rely on personalization to enhance customer experiences and gain a competitive advantage (Lambillotte & Poncin, 2023; Tong et al., 2020). For instance, Amazon's e-commerce platform recommends products based on users' purchase histories, browsing behavior, and demographic profiles; Netflix recommends movies and TV shows based on user ratings and viewing behavior; and social media platforms such as Instagram and TikTok prioritize content in their feeds according to users' past interactions and interests.

Recently, significant advances in sensor technology have emerged, including always-on connectivity, battery efficiency, integration capability, and miniaturization (Henrik-

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sen et al., 2018; Schultz et al., 2013; Schultz & Maedche, 2023; Yogev et al., 2023). Sensors can now be integrated into everyday devices such as smartphones, smartwatches, smart textiles, or even implants (Yogev et al., 2023). These developments create new opportunities to continuously record various human activities, such as eye gaze, heartbeat, facial muscle movements, or brain activities beyond medical applications (Henriksen et al., 2018; Schultz et al., 2013; Schultz & Maedche, 2023). The resulting biosignals can be processed and interpreted in real time via methods such as artificial intelligence (AI), including advanced signal processing and machine learning algorithms, thereby enabling deeper individualized personalization for information systems (IS) (Riedl et al., 2020). This trend is exemplified in fields such as personalized marketing, where means such as AI and wearables are proposed as a way forward to deliver personalized experiences, as highlighted in a bibliometric review of 383 publications employing performance analysis and science mapping by Chandra et al. (2022).

Building on this, we argue that products, services, and content on digital platforms can be delivered with a greater degree of individualization and utilization. This shift is driven not only by technical feasibility but also by customer demand for enhanced personalization and by organizations' potential to increase revenue (Arora et al., 2021). By continuously processing and recognizing biosignals, platforms can adopt a closed-loop architecture in which such signals are used to adapt platform behavior in real time. We refer to such systems as biosignal-adaptive platforms (BAPs). However, designing BAPs poses substantial challenges, as their scope and functionality can vary widely. This complexity spans multiple dimensions and characteristics that are not yet holistically understood. Understanding these dimensions and characteristics is crucial for researchers and practitioners to improve existing platforms and responsibly design future systems. Since this research stream is still emerging in the domain of electronic markets, there is a significant need for foundational conceptual work. Our literature review confirms that relevant research on BAPs in electronic markets remains scarce.

This paper advances the understanding of BAPs in electronic markets through three key contributions. First, we capture the complexity of BAPs from a technical-functional perspective by developing a framework, conceptualized as a morphological box, that delineates how real-time biosignals can be continuously recorded, processed, and used for closed-loop adaptation. The framework illustrates potential solution spaces across relevant dimensions and characteristics. Second, we conduct a systematic literature review in electronic markets research and map the three identified studies onto this framework, thereby illustrating the current state of BAPs, the configurations examined to date, and how such systems operate across diverse contexts, including e-commerce, auctions, and streaming services. Third, we highlight technical, methodological, ethical, and societal challenges associated with the design, implementation, and evaluation of BAPs, emphasizing the importance of responsible, human-centered, and interdisciplinary approaches. These challenges provide a basis for researchers and practitioners to systematically narrow the solution space defined by the morphological box when designing and applying concrete BAP solutions. Taken together, these contributions provide both an understanding of current BAP capabilities from a technical-functional perspective and guidance for their future development, with explicit consideration of ethical and societal implications.

The remainder of this paper is structured as follows: We first introduce key concepts related to adaptive systems and personalization. We then present our conceptualization of BAPs through the morphological box, followed by the method applied and the results of our literature review. We then discuss research opportunities before concluding the paper.

## Adaptive systems and personalization

The miniaturization, battery efficiency, and wireless connectivity of sensors enable an always-on connection to the internet, and thus a deep integration of sensors into human daily activities, ranging from smartphones, wearables (e.g., smartwatches), and integrated (e.g., smart textiles, smart environments) sensors over injected to even implanted sensors (Yogev et al., 2023). Wearable technologies, such as textile sensors, ink-based sensors, earables, or implants, are currently the subject of very active research and development (Röddiger et al., 2022). In addition, there are several initiatives surrounding *hearables*, i.e., wearable devices worn in or on the ear and connected to smart devices to perform functions such as medical monitoring, activity tracking, fall detection, or language translation, among others. *Smartglasses* provide the visual complement to these hearables.

As sensors are integrated into everyday life beyond medical applications, the data they collect can be used in various ways. For instance, biosignals — such as brain activity data — are used in sports science to adjust training plans and enhance training success (Rydzik et al., 2023). Moreover, vom Brocke et al. (2020) illustrate four key areas of how biosignals can provide benefit to IS research. First, signals can inform IS design. Second, biosignals can help researchers better understand the effects of IS use on individuals. Third, biosignals can help to better understand fluctuating user states, such as emotions. Lastly, such signals can serve as input for designing personalized, user-adaptive systems.

Being intensively used in practice and highly investigated across various academic fields (Statista, 2024), including economics, management, psychology, IS, and computer science, such personalization approaches, including adaptive systems, have been found to offer several advantages. For instance, Zhang et al. (2011) have shown that personalizing product recommendations can improve customers' decision quality. With advancements in AI, additional new and more sophisticated forms of personalization have been proposed (Gouthier & Kern, 2021; Vempati et al., 2020). Because personalization is a widely used concept across multiple academic fields and encompasses a broad range of interpretations, it is essential to clearly define what it means and how adaptive systems relate to it.

Personalization can be defined as "a process that changes the functionality, interface, information access and content, or distinctiveness of a system to increase its personal relevance to an individual or a category of individuals" (Fan & Poole, 2006, p. 183). Various forms of personalization are mentioned that differ based on the target of the personalization (i.e., individualized or category of individuals), the automation type (i.e., implicit: automatically by the system, or explicit: the user participates to provide system guidance), and what is personalized (i.e., the channel via which information is accessed, the content, the functionality, or the user interface of the system) (Fan & Poole, 2006).

While personalization describes the concept from an application-oriented business scenario, adaptation itself refers to the required system capability to use information from the user (i.e., the context of use, environment, and information about the user), to alter the system's behavior and tailor it to the individual user (Fan & Poole, 2006). These systems perform personalization implicitly and automatically (i.e., adaptive systems), compared to adaptable systems that rather rely on explicit user intervention (i.e., customization), or based on a mix of both types (i.e., mixed-initiative systems) (Findlater & McGrenere, 2004). Examples of such adaptive systems can be found across various research fields and application domains, including programming learning through serious games (Branthôme & Lallé, 2025), social rehabilitation (Tanaka et al., 2017), and smart home privacy and security (Wang et al., 2024).

Taking a closer look at the adaptive system's target of personalization, one can distinguish between systems that focus on categories of individuals and systems that focus on specific individuals (Fan & Poole, 2006) by relying on a wide range of user data (e.g., transactional, identity, demographic, attitudinal, or interaction data). However, findings from various research fields indicate that not only stable trait factors but also individual state factors, such as one's current cognitive load or emotional state, play a crucial role in how we perceive systems, how we act, and what demands we have on our working environment, including its technological devices (e.g., consideration of the current stress level on advice seeking; see Jensen et al. (2024)). To address these aspects, we argue that the unique properties of biosignals can be leveraged for deeper individualized personalization, enabling closed-loop BAPs with greater individualization and utilization.

## A morphological box for biosignal-adaptive platforms

To capture the complexity of BAPs, we developed a *morphological box* (see Table 1). Morphological analysis, as named by the Swiss astronomer Fritz Zwicky (Wissema, 1976), has been applied successfully across diverse contexts (Knaeble et al., 2023) and is described as "a creative way of illustrating all the potential solutions to existing problems in a structured format" (Kley et al., 2011, p. 3395). In this approach, a phenomenon is decomposed into key dimensions and the possible shapes (i.e., characteristics) each dimension can take (Wissema, 1976). This structured decomposition reveals a broad potential solution space and helps researchers and practitioners identify opportunities that might otherwise remain overlooked. These potential solutions can then be narrowed to a set of concrete solutions by logically combining feasible configurations and excluding those that are infeasible (e.g., for technical, methodological, economic, legal, or ethical reasons; see Kley et al. (2011)).

BAPs can continuously record, process, and interpret biosignals emitted by users to deliver appropriate adaptations (Schultz & Maedche, 2023). These systems operate in a closed-loop architecture in which target elements, such as affective-cognitive user states inferred from biosignals, guide system behavior and, in turn, influence user responses. We used a mix of top-down and bottom-up reasoning to derive the underlying characteristics for each dimension, as shown below. It is important to emphasize that we consider the dynamic interaction between the human user and the BAP as an *oscillating circuit* in which both entities influence each other (Schultz & Maedche, 2023). The fundamental conceptual framework of our morphological box is depicted in Fig. 1. Building on this conceptual framework, our morphological box comprises four central dimensions: (i) *activity and recording*, (ii) *processing and recognition*, (iii) *strategy and decision*, and (iv) *delivery and recipient*. Each dimension captures a fundamental aspect of the closed-loop process, defining the technical-functional solution space of BAPs.

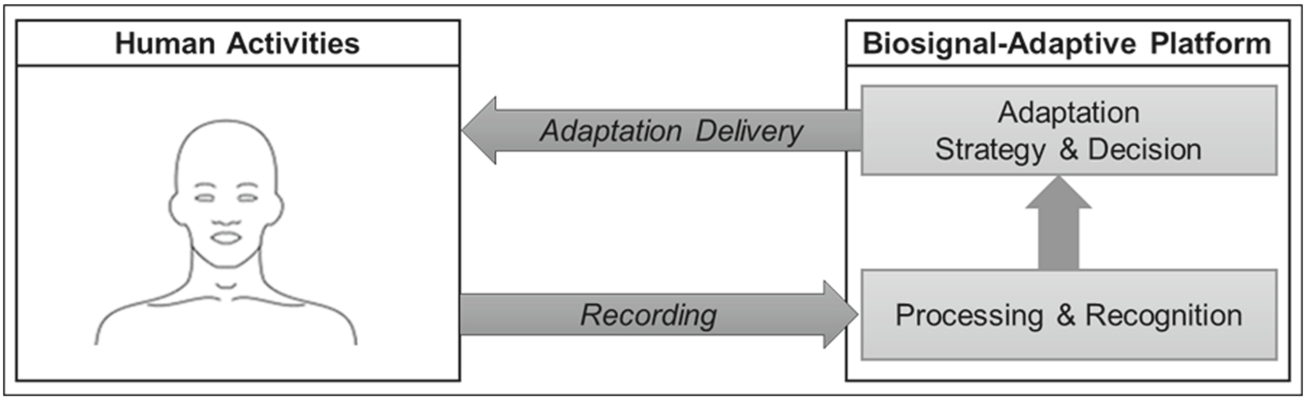


**Fig. 1** Conceptual framework

The following subsections explain each dimension and its corresponding characteristics in the morphological box.

## Activity and recording

The nervous system is fundamental for all human activity, both voluntary and involuntary. It connects the body and brain, allowing humans to sense, perceive, think, feel, and perform activities (Riedl & Léger, 2016). We base the characteristics in our morphological box on this grounding. In general, the nervous system consists of two interrelated parts. The central nervous system (brain and spinal cord; CNS) is responsible for neurological activities such as sensory processing, motor control, and higher cognitive functions that enable humans to perceive, interpret, and respond to their environment. The brain sends commands to the peripheral nervous system (PNS), which is distinguished into the autonomic nervous system (ANS) and the somatic nervous system (SNS). Here, the ANS regulates involuntary physiological activities such as heartbeat, pupil dilation, sweating, and digestion, which maintain essential bodily functions without conscious effort. In contrast, the SNS controls voluntary physical activities such as writing, sitting, standing, and picking up objects, enabling coordinated body movements under conscious control.

As humans perform CNS or PNS activities, their bodies generate biosignals. Biosignals can be conceptualized as autonomous signals produced by a living organism measured in physical quantities (Schultz et al., 2013; Schultz & Maedche, 2023). In our morphological box, the characteristics of biosignals are derived from the taxonomy of Schultz and Maedche (2023). Specifically, depending on the origin of a biosignal and the conditions or constraints of signal acquisition, various sensors can be used to measure acoustic, chemical, electrical, mechanical, optical, and thermal quantities. The resulting biosignals are classified as acoustic, chemical, electrical, kinematic, optical, and thermal. For instance, human activities such as speech, nonverbal sounds, and body noises can be captured by microphones and thus fall into the category of acoustic biosignals. Human activities, such as eye gaze, lip movements, or facial expressions, can be captured by cameras or webcams, resulting in optical biosignals. Moreover, blood volume changes in the microvascular bed of tissue (photoplethysmogram, PPG) can be derived either from camera-based optical recordings or from wearable devices such as smartwatches, fitness wristbands, or rings (Health Oy, 2024). Activities such as heartbeat or brain activity can be measured using surface electrodes, which form electrical biosignals. Notebooks at the workplace often include infrared sensors that enable the detection of body temperature (Lenovo, 2024), forming thermal biosignals. Even synchronous recording of high-dimensional biosignals, using a combination of these sensors to capture human daily activities, has become feasible and accessible to the research community (Meier et al., 2018).

## Processing and recognition

Subsequently, the received signals undergo processing and recognition, which often involve artifact removal, normalization, and feature extraction (Schultz & Maedche, 2023). Fusion strategies may be applied when multimodal biosignals are recorded (Schultz & Maedche, 2023). An important aspect of this process is accurately defining the target elements to be recognized and their corresponding human activities (Muñoz et al., 2021). Target elements are usually termed a construct; examples include cognitive load, flow, or stress, among others (Riedl et al., 2014).

For our morphological box, the targeted element is differentiated along states and traits. A state represents a temporary condition that fluctuates over time — for example, “I feel confident about this interview” or “I am nervous right now” describe states (Oxford Review, 2024). In contrast, a trait is a long-term characteristic of a person that forms part of their personality and influences their behavior, actions, and feelings. For instance, someone who describes themselves as "a confident person" or "an anxious person" is referring to a trait (Oxford Review, 2024). Next, building on Cacioppo and Tassinary (2007), we include four possible types of relationships between the target elements and the human activities in our morphological box, namely:

- *Many-to-many*: where multiple target elements are related to multiple human activities.
- *Many-to-one*: where multiple target elements are related to a single human activity.
- *One-to-many*: where one target element is related to multiple human activities.
- *One-to-one*: where one target element is related to a single human activity.

For recognizing target elements, our morphological box distinguishes three types: top-down approaches, which are knowledge-driven and logic-based (e.g., expert systems); bottom-up approaches, which are data-driven and statistical (e.g., machine learning); and hybrid approaches that combine both paradigms (Akerkar, 2026).

Machine learning algorithms have had an impressive impact on recognition performance (Bian et al., 2022). For instance, research contributed to the recognition of users' affective-cognitive states, such as flow, based on biosignals using machine learning (see e.g., Maier et al. (2019) — deep learning, Rissler et al. (2023) — shallow learning: Adaboost, C4.5, k-Nearest Neighbor, Naïve Bayes, Random Forest, Support Vector Machine-SVM). Notably, scholars have long had a tradition of creating features by hand, but such approaches are, among other things, highly dependent on individual experience in selection (Bian et al., 2022). Reflecting this shift, Bian et al. (2022, p. 5) stated that network models "based on convolutional computing (Münzner et al., 2017) or attentional mechanisms (Yang et al., 2020) for feature abstraction have dominated the approaches for data processing and presented the state-of-the-art recognition performance."

## Strategy and decision

Based on the outcomes of the recognition process, an adaptation strategy governs how the system responds to the detected target elements — that is, the recognized user states or traits — including whether its behavior should be modified or evolve over time (for instance, due to user fatigue). Various strategies have been explored to equip BAPs to convert biosignals into a control input for adaptation. Muñoz et al. (2021) developed a taxonomy and illustrative examples in the physiological computing research community, which we rely on for our morphological box.

### Classical control theoretic

Control-theoretic approaches can be differentiated into classical and modern variants (Muñoz et al., 2021), both of which are represented as characteristics in our morphological box.

Classical control entails established systems that have been in use for decades, such as the on-off (or bang bang) and proportional-integral-derivative (PID or any combination) controllers (Muñoz et al., 2021). The game "Space Connection" employs an on-off controller to activate or deactivate super-powers contingent upon players entering or exiting predefined thresholds for relaxation or attention level (Muñoz et al., 2016). To recognize the relaxation level, a respiration rate sensor was chosen, while the attention level was derived using a low-cost, electroencephalography-EEG-based brain-computer interface (BCI) (for a description of the state of the art and current trends in non-invasive BCI, see Edelman et al. (2025)). During the game, players are incentivized to work together as they need to regulate their own biosignals (i.e., either brain activity or respiration) to give their partner access to a unique superpower (i.e., either a time-manipulation power or a telekinesis power), which both players must use in a collaborative manner within different scenarios (i.e., three different physics-based puzzles) in order to succeed (Muñoz et al., 2016).

Moreover, other classical control-theoretic implementations have relied on PID controller designs, for instance, in the context of exergames (Muñoz et al., 2021). Exergaming refers to users playing any type of videogame that "requires physical exertion or movements that are more than sedentary activities and also include strength, balance, and flexibility activities" (Oh & Yang, 2010, p. 10). In an exergame developed by Sinclair et al. (2010), users sat on game bicycles — an interactive fitness bicycle — and pedaled to maintain a helicopter displayed on a computer screen at the desired altitude and fly through a 2D screen passage. PID control to adapt the exercise intensity level of the game based on continuous monitoring of humans' heart rate was presented as an effective means of supporting players in maintaining the desired level of exertion and for effective training (Sinclair et al., 2010).

### Modern control theoretic

An important aspect of modern control refers to robust control system design "that might not be optimal in the sense of minimization/maximization of some cost function, but would obtain a robust performance in the presence of some deterministic but unknown/bounded uncertainties" (Raol & Ayyagari, 2019, p. xv). Robustness means that a certain performance level is achieved and that uncertainties and model errors in relation to the control system in question remain within a certain range (Muñoz et al., 2021; Raol & Ayyagari, 2019).

We identified a modern, adaptive control approach as an illustrative example in the passive BCI context (Muñoz et al., 2021). Specifically, biosignals are highly individual (Labonte-Lemoyne et al., 2018). Following Labonte-Lemoyne et al. (2018), passive BCIs must be tailored to the individual to ensure proper functioning (e.g., Makeig et al. (2012)) by, for instance, using configuration tasks to individually adjust thresholds before a system is used (e.g., Johnson et al. (2011)). Hereby, two measurements are applied (Labonte-Lemoyne et al., 2018): one to measure the individual's responses to a task designed to elicit a particular state, and a second when the system has been tailored to the individual to actually use it. On the one hand, this is time-consuming and resource-intensive, and on the other, leads to solutions that do not respond to changes over time, such as fatigue or learning (Labonte-Lemoyne et al., 2018). Against this backdrop, Labonte-Lemoyne et al. (2018) suggested a dynamic threshold selection for the Tetris game by relying on a second biosignal to enhance the solution's robustness. In essence, what the second biosignal (i.e., automatic facial expression analysis used to derive emotional valence) would do is serve as an indicator of success for the adaptation based on the first biosignal (i.e., EEG signals used to derive cognitive load for speed changes within the Tetris game), so that it can be tailored to the individual.

Other modern control approaches include intelligent control (Muñoz et al., 2021). For instance, an illustrative example refers to the use of fuzzy logic in human-robot interaction for neurorehabilitation (Muñoz et al., 2021). Patients typically work together with a haptically controlled robot device to perform a specific task, such as reaching, "based on the paradigm "assistance-as-needed," where human and robot cooperate to successfully complete a task, minimizing the intervention from the robotic device and maximizing that of the human" (Rodriguez-Guerrero et al., 2017, p. 2). Despite their relevance to a person's motor control performance, factors such as boredom, discomfort, excessive physical work demand, lack of motivation, pain, and stress are typically addressed only marginally in existing research — a shortcoming also highlighted by Rodriguez-Guerrero et al. (2017). Drawing on a controller that uses fuzzy logic based on electrocardiography (ECG) and electrodermal activity (EDA) signals as well as contextual performance information, Rodriguez-Guerrero et al. (2017) simultaneously adapted the game difficulty and haptic assistance in a virtual reality task involving "catching falling drops" by manipulating the robot's end effector (i.e., the device at the end of a robotic arm). This allows for modulating perceived skill with haptic assistance and perceived challenge with game difficulty. To quantify and visualize the relationship between perceived challenge and perceived skill, the study also proposed a new metric.

Machine learning has emerged as another form of intelligent control (Siddique, 2013). One illustrative example for supervised and unsupervised learning can be found in myoelectric control (Muñoz et al., 2021), where muscle activity generated by human hand movements is used to offer manipulation commands (Oskoei & Hu, 2015). Oskoei and Hu (2015) explained that myoelectric control enables individuals with motor disabilities to interact with electronic devices, such as prostheses or video game consoles, provided that the system maintains long-term stable performance. The authors further noted that ensuring such stability is challenging because muscle activity may change over time, for example, due to fatigue. Against this backdrop, they have used both supervised and unsupervised adaptive schemes to deal with fatigue-based changes in myoelectric signals and change the SVM classification criteria to ensure stable performance in long-term usage. Notably, while supervised and unsupervised learning approaches have been successfully applied across a variety of domains in physiological computing, other types, such as reinforcement learning, remain underexplored yet show promise for future research (Muñoz et al., 2021).

## Delivery and recipient

Once an adaptation decision has been made, it must be determined how and where to deliver the corresponding adaptation. Thus, the last dimension of our morphological box concerns the delivery of adaptations to the recipient(s). In BAPs, the initiator and timing characteristics are fixed as system-driven and in real time during interaction, respectively, distinguishing these platforms from user-driven and retrospective alternatives (Fan & Poole, 2006). The remaining characteristics known in personalization (Fan & Poole, 2006) — form (i.e., what is adapted) and recipient (i.e., to whom it is adapted) — define how adaptation delivery is expressed in our morphological box.

Adaptation may take many forms (Labonte-Lemoyne et al., 2018), such as the difficulty of the task (Labonte-Lemoyne et al., 2018), the activation of features (Muñoz et al., 2016), or the visual output (Maior et al., 2018), to name but a few. For our morphological box, the "what facet" (see also Fan and Poole (2006)) includes adaptations of the access channel, content (e.g., tailoring recommendations, modifying information complexity, or filtering stimuli such as notifications), functionality (e.g., changing interaction modalities or enabling or disabling features), and interface (e.g., simplifying layout or adjusting visual density). The "to whom facet" differentiates between adaptations targeted at individual users and those directed at multiple users (similar to Fan and Poole (2006)).

**Table 1** Morphological box for biosignal-adaptive platforms

| Activity & Recording | Processing & Recognition | Strategy & Decision | Delivery & Recipient |
|---|---|---|---|
| **Human activity** | **Target element** | **Control theoretic** | **Form** |
| CNS activity | State | Classical-On-off | Access channel |
| PNS activity | Trait | Classical-PID | Content |
| **Biosignal** | **Relationship** | Modern-Adaptive | Functionality |
| Acoustic | Many-to-many | Modern-Intelligent | Interface |
| Chemical | Many-to-one | | **Recipient** |
| Electrical | One-to-many | | Individual |
| Kinematic | One-to-one | | Multiple |
| Optical | **Recognition type** | | |
| Thermal | Bottom up | | |
| | Top down | | |
| | Hybrid | | |

In sum, our morphological box comprises four dimensions and their underlying characteristics (see Table 1). This structure illustrates the potential solution space of BAPs from a technical-functional perspective and can serve as an analytical tool for comparing configurations in existing research. In the subsequent section, we apply this framework to categorize relevant studies in the field of electronic markets.

## Existing research on biosignal-adaptive platforms

We conducted a systematic literature review to identify existing research on BAPs. The following subsections present the underlying process and results.

### Process of systematic literature review

We followed established guidelines for conducting systematic literature reviews (Vom Brocke et al., 2009). In the first step, we determined our search strategy. The search string combined search terms from different perspectives, informed by prior reviews (i.e., Seitz et al. (2023) for recording and adaptation; Thenoz et al. (2024) for the environment). The overall search string is presented in Table 2.

Next, we selected databases and target outlets to conduct the search. We included the Basket of Eight Outlets (via EbSCOHost), Conferences in the IS and HCI field (i.e., via AIS eLibrary and conference websites for IS conferences of ICIS, ECIS, ACIS, AMCI, PACIS, WI Tagung, DESRIST, and HICSS, as well as via ACM Library filtered for CHI conference), and electronic markets-oriented outlets (i.e., Electronic Markets journal, Journal of Electronic Commerce via Web of Science). We conducted our search in September 2025 and searched for peer-reviewed articles in the libraries without date restrictions (i.e., all publications indexed up to September 2025). We applied the following filter criteria:

1. The article studies systems that process biosignals as input.
2. The article studies a form of platform, e-commerce, or e-market application.

**Table 2** Search string. *Within each row, terms are OR-connected; across rows, components are AND-connected*

| Component | Term |
|---|---|
| **Recording** | behavior* • bio* • brain • ECG • EDA • EEG • electro* • eye • facial • galvanic • gaze • GSR • heart • physio* • psychophysio* • skin • speech • voice |
| **Adaptation** | adapt* • aware • capture • feedback • intervention • personali* • sensit* • support* • targeting |
| **Environment** | ad • advertising • auction • bidding • “big data” • CRM • “customer relationship management” • “data analytics” • “digital business” • “digital service” • e-business • e-commerce • e-marketplace • e-procurement • e-services • e-shopping • “electronic business” • “electronic commerce” • “electronic data interchange” • “electronic marketplace” • “electronic procurement” • “electronic services” • “electronic shopping” • “internet-based commerce” • m-commerce • market • “mobile commerce” • “online business” • “online commerce” • platform • recommendation • “recommendation agent” • “recommendation system” • “recommender system” • “social commerce” • “ubiquitous commerce” • u-commerce • “virtual commerce” • v-commerce • “web-based commerce” • streaming • trad* |

3. The article studies systems that offer feedback on or adapt based on biosignals, representing closed-loop, control-theoretic BAPs as defined in our concept.

We illustrate our search process in Fig. 2, following the PRISMA framework (Page et al., 2021).

In total, our search yielded 2831 initial results across all databases when searching for our key terms in abstracts and keywords (275 hits on EBSCOhost, 1353 on AISeL, 3 on DESRIST, 1074 on ACMdL, and 126 on Web of Science). After screening the titles and abstracts against the filter criteria, we identified 157 articles for full-text review. Our final sample consisted of three relevant articles. A backward-forward search on these articles yielded no additional results. Two factors can explain the large number of false-positive articles. First, many identified articles do not represent a closed-loop, control-theoretic BAP but instead use biosignals as an analysis method to observe the impact of specific adaptations and personalizations in platforms (see e.g., Djamasbi et al. (2011)). Second, many publications present systems that do not target actual platforms or electronic markets. For instance, several articles focused on generic support systems but did not test them in market- or platform-like structures (see, for instance, Nacke et al. (2011) for an exploration of biosignal-adaptive game designs).

## Results of systematic literature review

In the following, we apply our morphological box to review the three identified articles and analyze their corresponding BAPs across the defined dimensions and characteristics, with each subsection summarizing existing research studies in specific electronic market contexts.

### Study I: Cognitive load-adaptive product recommendations

A prominent environment of digital platforms concerns the delivery of services and products through e-commerce. Specifically, the fields of advertising and neuromarketing have investigated integrating biosignals into digital platforms. In this context, we found the study by Tadson et al. (2023) that investigates cognitive load-adaptive product recommendations. Surface electrodes from EEG sensors (g.tec Research: a 32-channel device, based on wireless and gel-based active electrodes) are used to capture brain *activity* (CNS), forming an electrical *biosignal*. The data is processed

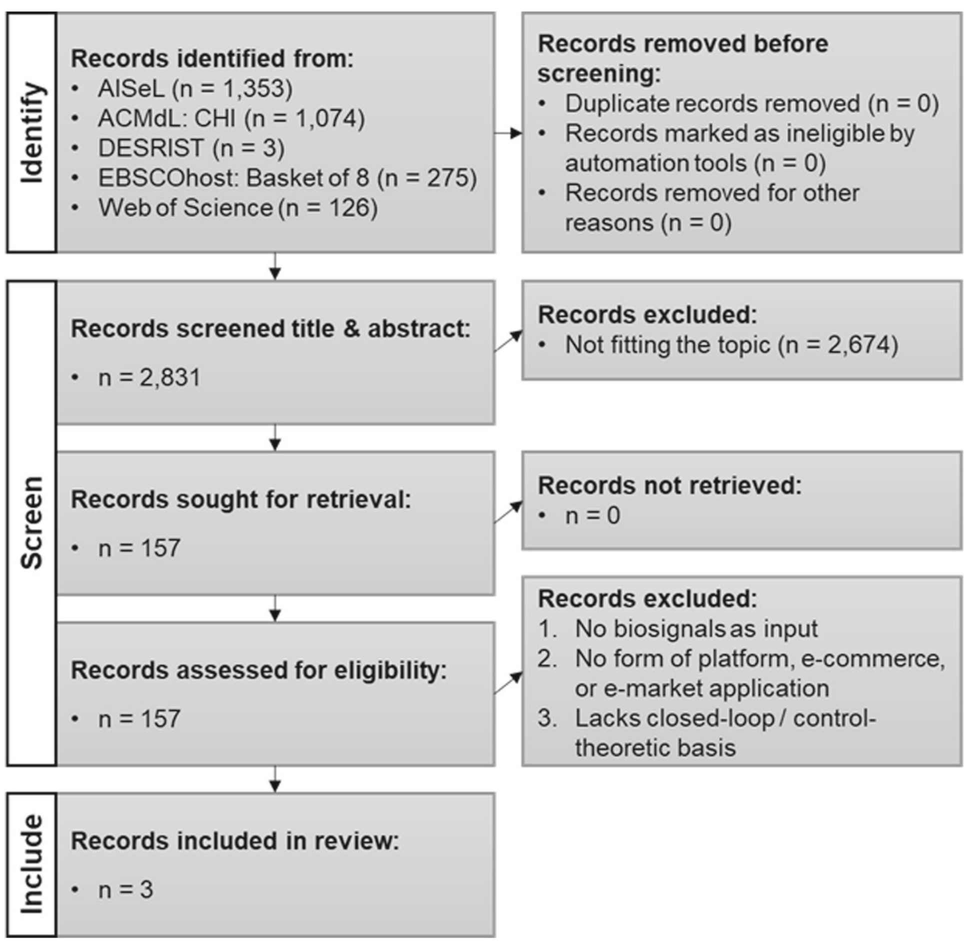


**Fig. 2** Report of the search process following the PRISMA framework (Page et al., 2021)

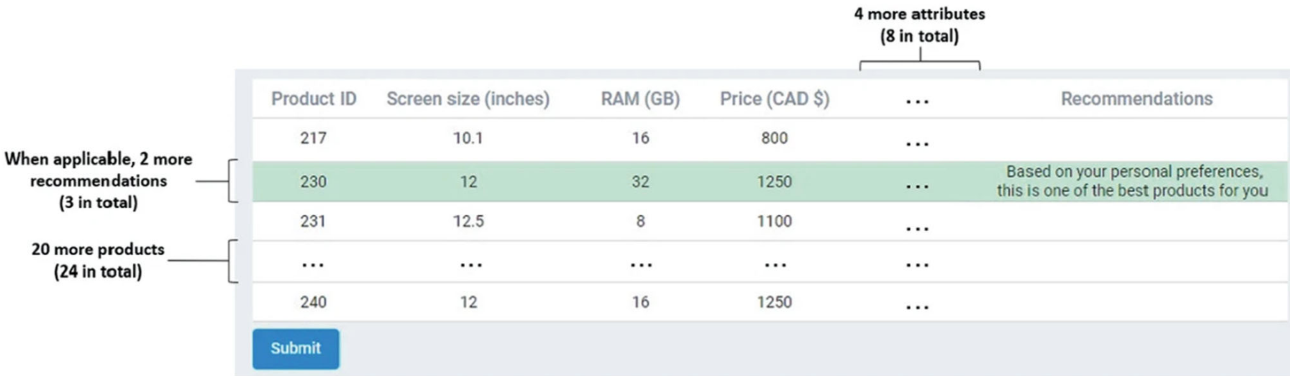


**Fig. 3** Cognitive Load-Adaptive Product Recommendations as visualized by Tadson et al. (2023). Figure taken from the original source and used for illustrative purposes to showcase the graphical user interface

by removing artifacts and filtering based on low-pass and high-pass filtering and a notch filter, among others. The *target element* is a cognitive state known as cognitive load. Hence, a one-to-one *relationship* is assumed as one target element is related to a single human activity. The *recognition type* is top down.

Specifically, cognitive load is classified as low (0), medium (1), or high (2) based on the average alpha-band power output over six-second intervals. The band-power thresholds for low and high cognitive load are calibrated for each participant using EEG signals recorded during a 0-Back and a 2-Back task, respectively. Moreover, a secondary logic assigns the value "3" if at least two of the last three cognitive load classifier values are "2" (i.e., confirming high cognitive load). Only when the value "3" is detected in the active time window (i.e., the first and last 12 s are suppressed to give the individuals the opportunity to read the entire product comparison matrix and react to any recommendations) does the system trigger the visual recommendation on the product comparison matrix. The adaptation strategy and decision employ a classical *control-theoretic* approach. The *form* of delivery symbolizes a user interface representation and provides a green highlight across the entire product row, as visualized in Fig. 3. The idea is to provide personalized recommendations when consumers are actually facing choice overload. Hence, the *recipient* is the individual. It is worth noting, however, that the study does not compare the actual impact on choice overload but rather proposes this neuro-adaptive logic for validation.

## Study II: Emotional arousal-adaptive adjustments in auctions

The second example we found in our literature review refers to the auction context. Specifically, Astor et al. (2013) investigated how auctions may be influenced when biosignals are incorporated. The authors use a financial game context and adapt the system in response to the affective states of market participants playing an auction game. In the study, market participants should become aware of their level of emotional arousal and improve their ability to maintain low levels, a form of emotion regulation, as excessive arousal can lead to detrimental financial decisions. Specifically, heart *activity* (PNS) is captured via a wireless ECG dry electrode chest-belt with surface electrodes, forming an electrical *biosignal*. The ECG data was processed by detecting the QRS complex to compute the most characteristic peaks, so-called R peaks, in the data, based on which heart rate is computed. The *target element* is the trader's emotional arousal level, an individual state. As only heart activity is associated with the target element, a one-to-one *relationship* is assumed. The *recognition type* used is top down.

Specifically, in-game arousal values are determined from heart rate in relation to the baseline period. Threshold values for the arousal level were calibrated in trial sessions and normalized on a scale from 1 to 5 (e.g., a value of 5 denotes the highest level and is achieved when the current heart rate is more than 15 percent higher than in the initial resting phase). The adaptation strategy and decision component employ a classical *control-theoretic* approach. The delivery *form* consists of content adjustments, specifically a variance of price estimates (i.e., the higher the individual emotional arousal of the player, the more difficult the game becomes) as well as a user interface adjustment in the form of a visual biofeedback element that continuously showcases a user's emotional arousal level. Biofeedback was offered in the form of an "arousal meter" in the right top corner of the game screen and based on the color of clouds (see also Fig. 4; the authors only provide a black-and-white screenshot) that were also shown on the screen (green, yellow, and red, with the latter color indicating the highest emotional arousal level). The adaptation targets an individual *recipient*. On this basis, Astor et al. (2013) were able to show how successful their game is in eliciting arousal and rewarding its down-regulation.


**Fig. 4** Emotional arousal-adaptive adjustments in auctions as visualized by Astor et al. (2013). Figure taken from the original source and used for illustrative purposes to showcase the graphical user interface

### Study III: Experience-adaptive communication and feedback in streaming

Our last identified example concerns the streaming environment. In particular, the Commons Sense system proposed by Robinson et al. (2022) performs heart rate sharing as a novel form of non-verbal communication and audience feedback for streamers in a game-streaming context (in an "Alien Shooter" scenario). In particular, the Commons Sense system captures heart *activity* (PNS), specifically the blood volume pulse (BVP) — the contractions of the heart in local blood vessels — via the webcams of participants watching from home, forming an optical *biosignal*. This approach was adopted due to its technical feasibility and minimal setup requirements for participants, enabling heart rate measurement with little effort. BVP was extracted by detecting minor variations in forehead coloration, which were then used to derive heart rate. The *target element* is not clearly defined, but Robinson et al. (2022, p. 3) state: "There is a pronounced opportunity in affective gaming to use the spectators' physiology for the sake of a rich overall experience, enhancing viewer/streamer enjoyment, connectedness, and engagement." We therefore define the overall experience as the target state. A one-to-one *relationship* is assumed, as one single human activity is associated with the target element. The *recognition type* refers to a top-down approach.

Specifically, before using the software, a calibration phase must be conducted to verify that the webcam is functioning properly and that other necessary conditions are met for consistent heart rate tracking (e.g., hair out of the face, a well-lit environment, and the webcam pointed directly at the face). Interestingly, this BAP combines data from the overall audience (i.e., those watching a Twitch stream) into a single metric: the mean heart rate among all spectators. The low and high thresholds for the heart rate were pre-tested during the entire implementation process. In the pre-tests, the average heart rate was generally between 40 beats per minute (bpm) and 140 bpm, which is why these values were chosen to indicate the low and high cases. On this basis, the following rule was introduced: 40 bpm means that the heart rate does not affect the game, while 140 bpm corresponds to a 100% effect on the game.

The adaptation strategy and decision component employs a classical *control-theoretic* approach. The delivery *form* comprises both functionality and user interface adjustments for the game being played. Functionality-wise, the difficulty is adjusted by modifying the speed, damage, and attack range of all enemies. The visual representations of the combined average heart rate are mapped to three components: a heart rate monitor (displayed in the upper-right corner of the screen), a difficulty gauge (also displayed in the upper-right corner indicating the effect of the audiences' heart rate on the game), and the environmental color intensity (a gradient ranging from a green, bright backlight for low average heart rate values to a red, dimmed backlight for high values). Additionally, an auditory representation enables the audience and the streamer to hear the heartbeat audio of the heart rate monitor. As those adjustments are directed to the streamer and the audience, the *recipients* of the adaptation are multiple people. Importantly, the Commons Sense designers implemented a high level of interdependence between the streamer and the audience, allowing spectators to choose whether the gameplay should be cooperative or competitive. Audience members could passively contribute by "just" sharing their heart rate data or actively influence the game by regulating their heart rate — either increasing it through physical activity or decreasing it through relaxation (e.g., deep breathing) — to help or hinder the player's progress. This design enables varying levels of engagement and grants the audience a sense of control over the gaming experience.

## Avenues for future research

The following section outlines future research directions and opportunities for the further development and application of BAPs. Given the scarcity of BAP studies in electronic market contexts — only three were identified in the previous section — this discussion draws on the broader literature from NeuroIS and related fields to establish a robust foundation for addressing technical, methodological, ethical, and societal challenges.

### Technical and methodological challenges

Building on the groundwork of Muñoz et al. (2021) and Schultz and Maedche (2023), we identified several challenges that define a future research agenda for BAPs.

### Sensor data quality and integration

Despite rapid advancements in sensor technology, acquiring high-quality sensor data in real-world conditions remains a major challenge. Key issues include artifacts stemming from biological (e.g., sweat, eye blinks), environmental (e.g., signal interference, lighting conditions), and technical (e.g., sensor malfunction) factors that introduce noise into the data (Islam et al., 2021); sensor calibration requirements (e.g., for eye tracking); and the collection of baseline data required for normalization (see also Schultz and Maedche (2023)).

An additional promising direction for future work lies in integrating multiple sensor sources. Some systems rely solely on a single source, such as heart rate or EEG, but combining multiple markers can significantly enhance a system's ability to recognize user states accurately. Multimodal integration enables a more comprehensive understanding of affective and cognitive states, potentially leading to more precise and effective adaptations. For example, Astor et al. (2013, p. 271) observed that "the current calculation of arousal is based on heart rate measurements solely[... and a] combination of several parameters will produce a more accurate and robust computation of arousal." This need is underscored by research in IS and electronic markets showing that complex mental processes are never the product of a single indicator. Instead, multiple indicators interact to produce a given mental process. This view is consistent with Riedl et al. (2014), who argue that many constructs relevant to IS research—such as attention, flow, or stress—emerge from complex, multilevel interactions between affective, cognitive, and physiological processes. They emphasize that such constructs should not be understood as purely cognitive or behavioral but rather as blended phenomena that manifest simultaneously at biological, psychological, and social levels. Accordingly, Riedl et al. (2014) stress the importance of multilevel conceptualization and operationalization, noting that valid measurement in NeuroIS requires integrating different types of indicators, including neurophysiological signals, self-reports, and behavioral data. Only through such complementary, multi-method approaches can researchers ensure high reliability, validity, sensitivity, and diagnosticity of measurements. This methodological pluralism, they argue, is essential for uncovering the true nature of complex user states and for advancing theory building in NeuroIS, as it captures the richness of human experience that no single indicator can represent alone.

### Machine learning issues and generative artificial intelligence

Machine learning poses a distinct challenge for BAP development, as most approaches assume access to extensive datasets for model construction (Muñoz et al., 2021). In practice, psychophysiological variables can exhibit substantial inter- and intra-individual variability, hindering the development of consistent, high-quality datasets for adaptive modeling (Muñoz et al., 2021). Moreover, Muñoz et al. (2021) emphasize that many studies face difficulties due to the absence of reliable ground truth for the variables analyzed (Saeed et al., 2018). For instance, even after extensive research, uncertainty persists regarding which feature-signal combinations are most indicative of emotion changes (Muñoz et al., 2021; Shu et al., 2018).

Looking ahead, future research should examine how emerging paradigms — particularly generative AI (GenAI) — may help address some of these challenges while potentially introducing new ones in the context of BAPs. Recent work by Banh et al. (2025a, b) further emphasizes the growing intersection between GenAI and NeuroIS research, providing insights that are directly relevant for BAPs. In their two complementary studies, the authors demonstrate that GenAI not only constitutes an object of investigation in NeuroIS — where it reshapes users' cognitive, emotional, and behavioral processes — but also serves as a powerful methodological tool. Specifically, GenAI can support the automation and personalization of experimental designs, data analysis, and stimulus generation, thereby improving scalability and responsiveness in biosignal-driven systems. At the same time, their findings highlight emerging research challenges, including trust calibration, cognitive offloading, and the ethical integration of GenAI into adaptive systems. Incorporating these insights into BAP research could accelerate the development of intelligent, human-centered adaptive technologies that are both scientifically rigorous and ethically aligned with user well-being.

### Adaptation delivery and implementation support

Another key challenge involves making informed decisions about adaptation delivery (Schultz & Maedche, 2023). The design space is extensive (Feigh et al., 2012; Schultz & Maedche, 2023), encompassing potential modifications to channels, content, functionality, and user interfaces. Given this breadth, systematically evaluating all possible configurations appears infeasible (Schultz & Maedche, 2023). Therefore, structured frameworks for prioritizing adaptation delivery options are essential to support researchers and designers in the effective development of BAPs.

Moreover, moving from design to implementation requires not only theoretical understanding, sensor availability, and signal processing expertise but also robust software tools to support the development (Muñoz et al., 2021). Examples such as NeuroPype[1] illustrate early progress, yet further improvements are needed to integrate consumer-grade and wearable sensors and to accommodate emerging media such as mixed reality (Muñoz et al., 2021).

[1] https://www.neuropype.io/

#### Evaluation and real-world validation

Finally, evaluating BAPs is a complex and demanding endeavor. As Schultz and Maedche (2023) emphasize, user responses are highly individual and context-dependent, which further complicates the evaluation process. Prior research recommends decomposing adaptivity and evaluating it piecewise. This body of work proposes layered evaluation frameworks and formative approaches that enable scholars and practitioners to assess adaptive systems (Paramythis et al., 2010). Importantly, such approaches do not preclude integrated, summative evaluations. On the contrary, assessing path dependencies and contextual constraints in field settings is essential to achieving real-world impact, while formative evaluations at each layer help improve system design. Nevertheless, not all layers can be isolated in every system, and their relative importance depends on the specific characteristics of the system under study (Paramythis et al., 2010).

For instance, Paramythis et al. (2010) identify five layers that should be considered when evaluating an adpative system: (a) collecting raw input data; (b) interpreting data, whereby raw data are assigned meaning; (c) modeling the current "world" state, which entails deriving new knowledge (e.g., about users and context) and integrating it into system models; (d) deciding upon adaptation, where the system determines whether and how to adapt based on the current "world" state; and (e) applying adaptation, referring to the enactment of the selected adaptations in the user-system interaction. To support scholars or practitioners in selecting appropriate evaluation methods across these layers, Paramythis et al. (2010) also provide an overview and discussion of evaluation goals, criteria, and methods for each proposed layer.

Moreover, most existing studies rely on controlled laboratory settings. To ensure real-world relevance, future research should increasingly adopt longitudinal and field-based designs. Such approaches will be essential for understanding how BAPs perform over time and across diverse environments. Longitudinal studies can also shed light on long-term impacts on user behavior, performance, and well-being. Moreover, cultural and demographic differences must be considered. Given that emotional expression and cognitive processing differ across regions, future studies should explore these influences and ensure that adaptive technologies are inclusive.

A recent contribution by Balapour and and Riedl (2025) further underscores the importance of establishing ecological validity in NeuroIS and biosignal-based research. They demonstrate that results obtained under controlled laboratory conditions often suffer from limited generalizability if the measurement setting, stimuli, or participant behavior differ substantially from real-world environments. Drawing on an extensive review of 42 NeuroIS studies, Balapour and Riedl (2025) show that only a minority adequately address the verisimilitude and veridicality of their designs — that is, the extent to which experimental tasks, contexts, and responses resemble and predict real-life phenomena. Their proposed roadmap highlights strategies to enhance ecological validity, such as using less intrusive measurement tools, employing dynamic and contextually embedded tasks, and integrating field-based or mixed reality approaches. For adaptive biosignal systems, following these recommendations can ensure that laboratory findings translate into robust, reliable performance in real-world contexts.

### Ethical and societal considerations

Ethical and sustainability-related topics remain less prevalent in electronic market research (Nahr & Heikkilä, 2022), despite repeated calls for more research from this perspective (see Alt and Klein (2011); Pucihar (2020)). Nahr and Heikkilä (2022) examined the diversity of research on electronic markets, utilizing text mining and bibliometric analysis, and demonstrated, among others, that this type of research is still vastly underrepresented. Yet, as a prerequisite for bioisignal-based technologies to become established in electronic markets, both practice and academia must adhere to certain standards and ethical norms. The unique properties of biosignals cannot only be utilized in BAPs for a higher degree of individualization and utilization (Fan & Poole, 2006), but also raise significant ethical and privacy concerns, highlighting the need for responsible design (Fairclough, 2014; Yuste et al., 2017). As Karwatzki et al. (2022) also noted, their study examined privacy risks only in the context of innovative apps, leaving ample room for future research to explore other settings such as social networking, e-commerce, or any service offering personalized content and recommendations. Building on Yuste et al. (2017), we aim to demonstrate how the unique properties of biosignals present novel challenges in this regard or exacerbate existing concerns.

#### Privacy, consent, and data governance

The use of internet-connected technology based on biosignals enables a person or organization to monitor or even manipulate a human's mental experiences, making solutions for scenarios like targeted advertising or matching potential partners much more powerful (Yuste et al., 2017). However, research like Nieto-Reyes et al. (2017) demonstrate that it is already possible to detect early signs of cognitive impairment associated with Alzheimer's disease by analyzing the mobility patterns of individuals who carry a smartphone while moving freely.

Future research must therefore establish robust frameworks for privacy, informed consent, and governance of biosignals. To this end, scientists could build on existing frameworks that promote ethical and socially desirable science and innovation (Yuste et al., 2017) and place them in the context of BAPs. Due to the interdisciplinary and socio-technical nature of the IS discipline, its researchers seem particularly suited to such a task. An opt-out is proposed by research as the default option for any neural data (Yuste et al., 2017). It would require individuals to explicitly opt in to the sharing of neural data from any device. Doing so would embed a secure and safe process, with a consent process clarifying by whom the data will be used, the purposes for which it will be used, and over what period of time. Another safeguard could be to strictly regulate the sale, commercial transfer and use of neural data in order to "limit the possibility of people giving up their neural data or having neural activity written directly into their brains for financial reward — [such regulation] may be analogous to legislation that prohibits the sale of human organs, such as the 1984 US National Organ Transplant Act" (Yuste et al., 2017, p. 161).

For the protection of human privacy, computational techniques like federated learning and differential privacy are also suggested (Yuste et al., 2017). In the IS literature, for example, Adam et al. (2017) describe biosignal adaptation as an important component of future stress-sensitive enterprise systems. Importantly, in their paper, they also explicitly refer to potential privacy issues, ethical acceptability, and some initial solutions (e.g., local (pre)processing of sensor data instead of transmission to online platforms). Moreover, data can be tracked and audited using blockchain-based technologies, and 'smart contracts' can enable transparent control over data usage without a central authority (Yuste et al., 2017). Finally, more transparency about what remains private and what is shared would be made possible by open data formats and open source code (Yuste et al., 2017). Future research could build upon these ideas to explore potential ethical and privacy issues of related solutions in greater depth.

### Agency, identity, and neurorights

A further critical area of concern lies at the intersection of neurotechnology and AI. On the positive side, advances in both fields could revolutionize the treatment of many diseases, such as brain injuries or paralysis, and improve human life (Yuste et al., 2017). But the resulting technology could also reinforce social inequalities and give organizations, hackers, public authorities, or other third parties new forms to make use of and manipulate humans. It could also radically change private mental life, individual agency, and the understanding of humans as beings tied to their bodies. For instance, Yuste et al. (2017, p. 162) stated that in the study by Klein et al. (2016) "a man who had used a brain stimulator to treat his depression for seven years reported in a focus group that he began to wonder whether the way he was interacting with others — for example, saying something that, in retrospect, he thought was inappropriate — was due to the device, his depression or whether it reflected something deeper about himself."

To address these concerns, scholars argue for the protection of individual identity (i.e., our physical and mental integrity) and agency (i.e., our ability to determine our own actions) as *fundamental human rights* (Yuste et al., 2017). Proposed measures include (i) the inclusion of such 'neurorights' in international treaties, (ii) international conventions defining prohibited acts associated with neurotechnology and machine intelligence, and (iii) the safeguarding of humans' right to be educated about the potential cognitive and emotional impacts of neurotechnologies (Yuste et al., 2017).

### Augmentation and responsible design

We also emphasize that future solutions are likely to play an important role in enhancing human-AI collaboration. By continuously adapting to the user's state, these systems can facilitate more effective human-AI interactions, leading to improved decision-making, problem-solving, and creative processes. Research in this area should focus on developing frameworks for seamless and symbiotic interactions, where both humans and AI systems learn and adapt to each other over time. These frameworks and related recommendations should align with existing guidelines for human-AI interaction (e.g., Amershi et al. (2019)).

At the same time, we also see the downsides that such developments could have. For instance, unlocking enhanced neurotechnologies could put pressure on humans to drastically increase their endurance, mental, or sensory abilities, which would likely subsequently lead to a shift in social norms, trigger issues of equal access, and pave the way for novel forms of discrimination (Yuste et al., 2017). Responsible design principles are therefore essential. The aforementioned guidelines and frameworks must also contain clear restrictions on use contexts. Since it is easy to envision an *arms race* (e.g., to improve the mental capabilities of soldiers), we also advocate strict regulation of such technologies for military purposes (Yuste et al., 2017).

## Conclusion

This article introduced BAPs that continuously sense, interpret, and respond to users' biosignals. They extend the established personalization paradigm from behavioral and contextual data toward a more fine-grained personalization, leveraging real-time biosignal data. To conceptualize this phenomenon, we present a conceptual framework and a morphological box comprising four key dimensions: *(i) activity and recording, (ii) processing and recognition, (iii) strategy and decision,* and *(iv) delivery and recipient*. This framework adopts a technical-functional perspective and structures the potential solution space for BAPs. It can be used to characterize and analyze BAP configurations within the broader discourse of personalization in IS research. Our systematic literature review revealed that, despite increasing technological feasibility and real-world relevance, research on BAPs in the context of electronic markets remains scarce. Only a few studies address these systems in contexts such as e-commerce, auctions, and streaming, underscoring the field's early stage and the need for future research. While this article conceptually advances the understanding of the potential solution space of the underlying technical-functional building blocks of BAPs, it equally emphasizes that their responsible design should depend on governance, user empowerment, and ethical safeguards. These challenges provide a basis for researchers and practitioners to systematically narrow the solution space defined by the morphological box when designing and applying concrete BAP solutions. Importantly, we explicitly reject any deterministic assumption that biosignal-adaptive information technology alone ensures user benefit; instead, achieving positive outcomes will require following a socio-technical approach. The morphological box also invites empirical validation across diverse use cases, and our review may not fully capture interdisciplinary work beyond the IS field. These limitations highlight opportunities for future work to test and refine our framework.

In conclusion, realizing BAPs will require interdisciplinary collaboration across domains, including computer scientists, social scientists, engineers, humanities scholars, neuroscientists, and policymakers, to ensure that biosignal-driven personalization enhances, rather than constrains, human agency and equality. By positioning BAPs as socio-technical systems embedded in broader economic and ethical contexts, we invite future research to balance innovation with reflection — advancing not only what such platforms *can* do, but also what they *should* do in the future of electronic markets.

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