Title

Expectation violations, expectation change, and expectation persistence:
The scientific landscape as revealed by bibliometric network analyses

Authors

José C. García Alanis^{1,*}, Anna Enrica Strelow¹, Martina Dort¹,
Hanna Christiansen¹, Martin Pinquart¹, Christian Panitz^{1,2,3}

Author information

[1] University of Marburg, Department of Psychology,
Gutenbergstr. 18, 35032 Marburg, Germany

[2] Department of Psychology,
University of Leipzig, Leipzig, Germany

[3] Center for the Study of Emotion and Attention,
University of Florida, Gainesville, FL, United States

[*] Correspondence regarding this article should be addressed to:
José C. García Alanis,
Department of Psychology, University of Marburg,
Gutenbergstr. 18, 35032 Marburg, Germany.
e-mail: jose.alanis@staff.uni-marburg.de

ORCID

José C. García Alanis: 0000-0003-3459-222X; Martina Dort: 0000-0003-3837-3825;
Martin Pinquart: 0000-0003-4496-4250; Christian Panitz: 0000-0001-6692-8555

Author contributions

Original idea and conceptualization: Hanna Christiansen, Christian Panitz, Martin Pinquart, José C. García Alanis, Anna Strelow, Martina Dort; Literature search: José C. García Alanis; Data pre-processing: José C. García Alanis, Christian Panitz, Hanna Christiansen, Martin Pinquart, Anna Strelow, Martina Dort; Formal analysis: José C. García Alanis; Visualization: José C. García Alanis; Writing – original draft preparation: José C. García Alanis; Writing – review, editing, and approval of final draft: José C. García Alanis, Christian Panitz, Martin Pinquart, Hanna Christiansen, Anna Strelow, Martina Dort

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Data availability

All analysis scripts and data needed to reproduce the reported results are available at:
<https://osf.io/ymk8q/>

Abstract

Expectation violations occur when there is a discrepancy between expected and perceived events or experiences. However, expectations often persist despite disconfirming evidence. Therefore, research on expectation violations, expectation change, and expectation persistence has been conducted in several fields of psychology with wide-ranging theoretical assumptions and empirical considerations. In the present review, we analyzed how these research fields relate to each other via bibliometric network analyses. For this purpose, we conducted a systematic literature search to identify scientific publications on expectation violations, expectation change, and expectation persistence. The literature corpus was then quantitatively analyzed using similarity measures that allow a data-driven classification of publications into groups, revealing their conceptual, theoretical, and empirical commonalities. Our results indicate that many influential publications have focused on finding reactivity measures (e.g., brain activation) to the discrepancy experienced between expectations and outcomes. Furthermore, these measures have been used to assess when and to which degree learning and behavioral adaptation (i.e., expectation change) takes place. We discuss the potential application of these measures for understanding expectation violations in more complex settings (e.g., social interaction) as well as phenomena such as expectation persistence. The goal of this review was to foster interdisciplinarity in psychology, enabling scientists and practitioners to identify new topics, promising empirical approaches and previously neglected variables.

Keywords

expectation violations, expectation change, expectation persistence, prediction error, bibliometric review

Introduction

Expectations can be defined as conditional beliefs about the probabilities of future events, experiences, or information (cf. Hoorens, 2012; Panitz et al., 2021). Expectations vary from (more or less) possible to certain (Roese & Sherman, 2007), they can be more or less explicit (i.e., conscious; Proulx & Inzlicht, 2012), and they may focus on heterogeneous contents (cf. Laferton et al., 2017). For instance, individuals can harbor expectations about their own behavior and experience in a potentially demanding situation, but they also can have expectations regarding characteristics of the situation itself, or about others' reaction to one's own behavior. As such, expectations are related to a wide spectrum of anticipatory mechanisms ranging from basic perceptual and motor functions (de Lange et al., 2018; Yon et al., 2019) to highly elaborated, and sometimes stereotypical, beliefs about others (Dort, Strelow, Schwinger, et al., 2020; Kotzur & Wagner, 2021). Due to their probabilistic nature, expectations often prove inaccurate, or even entirely erroneous, in the face of disconfirming information. Expectation violations therefore occur in the case of discrepancy between expected and perceived situational outcomes. It is a widely accepted notion that the processing of expectation violations is necessary for learning and effective interaction with the environment (cf. Gollwitzer et al., 2018; Rief et al., 2015). In addition, research indicates that expectation violations are of central relevance for many domains of psychology (Pinquart, Endres, et al., 2021; Pinquart, Rothers, et al., 2021), as they very often enable individuals to detect ongoing deviations from internally represented goals (Roese & Sherman, 2007), to adapt goal-directed behavior (Holroyd & Coles, 2002), and to regulate experience in line with situational characteristics (Clark, 2013; Panitz et al., 2021; Pinquart, Endres, et al., 2021), for instance, when actions fail to lead to expected outcomes (cf. Sambrook & Goslin, 2015).

Different theoretical models have been proposed to explain how organisms cope with expectation violations (cf. Pinquart, Endres, et al., 2021 for review). Here, the discrepancy experienced between expectation and disconfirming evidence is often referred to as prediction error (Friston, 2009; Rescorla & Wagner, 1972; Schultz et al., 1997). A large body of research indicates that the degree to which expectation violations trigger compensatory organismic, cognitive, emotional, and motivational responses scales proportionally to the magnitude of the prediction error (Den Ouden et al., 2012; Hajcak, 2012; Holroyd & Coles, 2002; Sambrook & Goslin, 2015). Furthermore, it has been proposed that one of humans' core motives is to make future expectation violations less probable (Clark, 2013; Proulx & Inzlicht, 2012), as they often evoke aversive emotional states (Proulx et al., 2012), enhance control demands (Shenhav et al., 2013), and might threaten individuals' self-concept (Brandtstädter & Greve, 1994; Korn et al., 2012; Pinquart & Block, 2020). Previous research (Panitz et al., 2021; Rief et al., 2015) proposes that minimizing future expectation violations can be achieved by adaptively adjusting expectations as a function of the prediction error, leading to updated versions of those expectations that integrate previous and current expectation-disconfirming information. Evidence for this process is provided in situations in which individuals employ performance feedback to proactively recruit control resources and prepare for comparable situations in the future (Bejjani et al., 2020; Cavanagh et al., 2010), but also when the goal-directedness of unfavorable choices is questioned in order to keep maladaptive habits from forming and being maintained (Gillan et al., 2015; McKim et al., 2016). In this line of research, particular attention has been paid to event-related transient fluctuations (i.e., Event-Related Potentials - ERPs) in scalp-recorded electroencephalogram (EEG) following expectation violations, such as the Feedback-Related Negativity (FRN, Miltner et al., 1997) and the Error-Related Negativity (ERN, Gehring et al., 1993; or fronto-

central negativity – NE, as in Falkenstein et al., 1991). It is believed that FRN and ERN reflect endogenous alarm signals that allow individuals to identify deviations from internally represented goal states (i.e., expectations) and adjust their behavior and/or expectations accordingly (Holroyd & Coles, 2002; Sambrook & Goslin, 2015), thus providing physiological correlates for the processing of expectation violations across various psychological domains (cf. Weinberg et al., 2015) and situational embeddings (cf. García Alanis et al., 2019; Mueller et al., 2014).

Often however, individuals do not update their expectations after they have been violated by situational outcomes (Panitz et al., 2021; Proulx et al., 2012; Roese & Sherman, 2007). Such expectation maintenance can be advantageous when the outcomes obtained could be disregarded as likely noise (Hohwy, 2017), when avoiding or attenuating negative affect after worse-than-expected experiences (Proulx et al., 2012), or when expectations need to be robust because they relate to values and positive beliefs that individuals hold about themselves or the world (Pinquart & Block, 2020). Conversely, maintaining expectations despite disconfirming evidence can also have negative consequences for oneself (e.g., psychopathology; Kube et al., 2017, 2019) or others (e.g., stereotypes; Kotzur & Wagner, 2021). For instance, rigid, negative expectations have been identified as one essential factor involved in the development and chronicity of mental disorders (Craske et al., 2014). However, the precise cognitive (Pinquart, Rothers, et al., 2021) and neural (D'Astolfo & Rief, 2017) mechanisms that underlie coping with expectation violations remain controversial. Research on coping with expectation violations has been conducted in several fields of psychology (e.g., general, social, or consumer psychology; Pinquart, Endres, et al., 2021) and with varying theoretical and empirical foci (e.g., neurophysiological processes: D'Astolfo & Rief, 2017; expectation persistence versus change: Panitz et al., 2021; coping with associated negative emotions: Proulx & Inzlicht, 2012). As there is considerable heterogeneity and often little exchange between these different research domains, there is a need to analyze how different approaches interrelate, and which studies have been most influential in the field. Therefore, a comprehensive overview of the conceptual structure and theoretical commonalities of a growing body of research on expectation violation, change, and persistence is needed to help inform future studies and identify new areas of potential application.

To address these issues, the present study pursued a science mapping approach by implementing bibliometric analysis techniques (Diodato & Gellatly, 2013) to quantitatively analyze the conceptual patterns that emerge in scientific publications on expectation change and maintenance in the context of expectation violations. More precisely, we analyzed manuscript keywords of scientific articles and their reference lists to compute similarity and network analysis measures, provide a data-driven classification of bibliographic objects into groups, and reveal commonalities and relationships within and between the research clusters we identified (cf. Zupic & Čater, 2015). A bibliometric approach has methodological implications and advantages that complement other types of review studies (cf. Andersen, 2019; Dort, Strelow, French, et al., 2020). First, a bibliometric review allows a broader perspective, because researchers can analyze larger bodies of literature than in purely qualitative reviews, with the latter often focused or limited in scope, and based typically on a few dozen articles. Second, a bibliometric review provides the opportunity to identify higher-order patterns that offer context and location for more focused and detailed reviews in the broader field. Third, as the concept of expectation violation is relevant for many fields of research, it is likely that a traditional narrative review would miss important, perhaps underrepresented, clusters of literature. Furthermore, as traditional reviews are

grounded in their authors' experience and expertise in the field, their assessment of the relationships between clusters of literature might be more subjective. This also makes traditional reviews susceptible to multiple sources of bias, such as the author's degree of specialization in the field, and, more generally, that of citation bias toward work central to the authors' field (Mullen & Ramírez, 2006). In contrast, bibliometric analyses follow fully replicable and explicit data gathering and analysis plans, making bibliometric reviews less susceptible to researchers' degrees of freedom, and leading to more robust and objective estimates for evaluating the relationships within and between clusters of literature (cf. Archambault et al., 2009).

The aim of this study was to provide a structural overview of the scientific avenues currently in the field of expectation violation research. To the best of our knowledge, this is the first bibliometric review in expectation-violation literature. It builds up on existing systematic and meta-analytical reviews focusing on different theoretical models of expectation violation (Pinquart, Endres, et al., 2021), as well the brain structures (D'Astolfo & Rief, 2017) and personal or situational variables (Pinquart, Rothers, et al., 2021) that support expectation persistence or change. The present study is intended to help researchers navigate the field and identify promising, and perhaps underdeveloped, research domains. By finding links and commonalities in the field of expectation violation research, the present study is also meant to facilitate interdisciplinarity, enabling scientists and practitioners to look outside their field-specific box. Our goal is to provide guidance for the discovery of alternative approaches, helping researchers to identify important topics and variables that might have been neglected otherwise.

Method

Literature search

The Social Sciences Citation Index (SSCI), which is available online through the Web of Science (WoS), was selected as our primary data source. It features more than 500 journals related to psychological science. In addition, it covers a wide spectrum of sub-disciplines and interdisciplinary research fields related to human behavior, cognition, and affect. We included publications focused on the biological and neuroscientific bases of behavior, as well as research focused on social, personality, emotional, and motivational phenomena along with possible implications for clinical, developmental, and educational fields of application.

The SSCI was searched on December 16, 2020, using the Boolean search term presented in Table 1. The search was limited to documents published between 1990 and 2020 (December 16) within the WoS category of psychology. The search term was designed to seek the term expectation violation (or variations thereof, such as violation of expectations, violated expectations, etc.) in the title, abstract, author keywords, and keywords plus fields of each document. The search included documents focusing on the impact of expectation violation on behavior and experience, i.e., whether the violation of expectations induced learning or change, or whether behavioral, cognitive, or emotional patterns persisted afterwards. This was achieved by searching for combinations of words with the stems “expect”, “violate”, “change”, and “persist” (but also variations of the same, see below) in scientific publications using wildcards (i.e., “*”) combined with the NEAR/0 and NEAR/1 Boolean operators in WoS. Thus, the Boolean search term $TS=((expect*)NEAR/0(violate*))$ would lead to hits in publications in which “expectation violation” and “expectancy violation” were provided as keywords, as they share the same word stems and are not separated by any word (i.e., are NEAR/0). In contrast, the search term $TS=((violate*)NEAR/1(expect*))$ would lead to hits in publications in which “violated expectations” was provided as a keyword, but also publications with “violation of expectations” as keyword, as they share the same word stems and are separated by a maximum of one word (i.e., are NEAR/1). Topic terms closely related to expectation violation were also included in the search (e.g., prediction error). To identify terms closely related to expectation violation, expectation change, and expectation persistence, we first screened literature on theoretical models of expectations and expectation violations for potentially relevant terms (cf. D’Astolfo & Rief, 2017; Gollwitzer et al., 2018; Rief et al., 2015). Second, we analyzed project reports from 16 PhD students enrolled in the local Research Training Group on expectation violations (DFG Research Training Group 2271 “Breaking Expectations”) who had provided information about their projects (e.g., theoretical background, hypotheses). The final list of search terms (see **Table 1**) was created by relying on the collected terms and discussion among the present study’s authors.

Table 1

Search string used to identify records of interest in the Social Sciences Citation Index (SSCI)

TS = (

(

("expect*" **OR** "predict*" **OR** "anticipat*" **)**

NEAR/0

("violat*" **OR** "falsif*" **OR** error* **OR** "disconfirm*" **OR** "devia*" **OR** "discrep*" **OR** "inconsist*" **OR** "incongruen*" **OR** "diverg*" **OR** "dissonan*" **)**

OR

("violat*" **OR** "falsif*" **OR** error* **OR** "disconfirm*" **OR** "devia*" **OR** "discrep*" **OR** "inconsist*" **OR** "incongruen*" **OR** "diverg*" **OR** "dissonan*" **)**

NEAR/1

("expect*" **OR** "predict*" **OR** "anticipat*" **)**

)

)

AND

TS = (

(

"maint*" **OR** "stabil*" **OR** "persist*" **OR** "adapt*" **OR** "adjust*" **OR** "updat*" **OR** "learn*" **OR** "consolidat*" **OR** "chang*" **OR** "modif*" **OR** "accomodat*" **OR** "compensat*" **)**

)

)

AND

PY = ((1990-2020))

AND

WC = (PSYCHOLOGY)

Note. TS = Web of Science search field "Topic" (title, abstract, keywords).

* = wild card for word ending (e.g., *expect** includes expectation, expectations, expectancy, etc.).

NEAR/0 = Key terms need to be located by located next to each other (e.g., expectation violation).

NEAR/1 = Key terms can be separated by no more than 1 word (e.g., violation of expectations).

PY = Publication year range.

WC = Web of Science category.

Data preparation and analysis

Bibliometric analyses enable us to compute quantitative measures of relatedness between bibliographic objects (e.g., journal articles) based on their bibliographic characteristics, such as reference lists, authors, or keywords (cf. Zupic & Čater, 2015). The aim of the present study was to provide an overview of the seminal work, psychological phenomena, and concepts that have influenced expectation violation research. Data was therefore screened to identify different spellings and misspellings in the document identifiers (i.e., author names, document titles, journal names, etc.) prior to analysis. This was done to filter out potential duplicates and merge them into a single entry, thus minimizing the danger of artefacts caused by repeatedly including single documents in the analysis (i.e., false positives). In addition, documents with fewer than 10 citations were excluded from analyses, as they would increase the complexity of the results without representing highly influential nodes in the networks.

Analysis of keywords and trend topics

Keywords resulting from the SSCI search were pre-processed as follows. First, all keywords were transformed to lower case to more easily identify duplicates. Generic terms (e.g., “method”, “construct”), words that do not denote a concept such as the names of countries or nationalities (e.g., “American”), and overly vague research methods or disciplines (e.g., “behavioral experiment”, “cognitive neuroscience”) were excluded. Common single terms were converted into the abbreviated synonyms commonly used in the field (e.g., “Cognitive Behavioral Therapy” as “cbt”, “Event-Related Potential” as “erp”) to avoid special characters and long single-term overlap in the visualizations. Plural words were converted into their singulars (e.g., “expectations” to “expectation”) to avoid separate nodes for plural and singular forms of the same underlying term. Finally, the words “expectancy” and “expectation” were merged to the single term “expectation”. In practice, use of the expectation and expectancy terms overlaps in the psychological literature, suggesting that quantitative effects arising from distinguishing these terms would be spurious in nature (cf. Andersen, 2019). The same was done with the terms “expectation violation”, “expectancy violation”, “violation of expectations”, and “violated expectations” (i.e., all merged into “expectation violation”). All analysis scripts and data needed to reproduce the results are available at: <https://osf.io/ymk8q/>. To visualize important keywords and, by extent, important topics of research in the literature corpus, we computed the frequency of each keyword in the Keywords Plus® field of each document for each year in the time range 2010-2020. We limited the time range to 2010-2020 to reveal emerging and influential topics in the literature. Trend topics were computed by calculating the median year of a appearance for each keyword based on these frequency measures. Further bibliometric analyses were structured along two major analytical steps: Co-citation and bibliographic coupling.

Co-citation analyses

We measured the relevance of bibliographic objects (e.g., journal articles) for expectation violation research based on how often these objects appeared together in the reference lists of other bibliographic objects (i.e., were co-cited) within the entire time range (i.e., 1990-2020) of our literature search (McCain, 1990; Small, 1973). Thus, the units of analysis here are journal articles (or books) typically cited by articles identified through

our literature search. It is important to note that these documents are not necessarily part of our literature search results but are rather found in the reference lists of that body of research. The rationale of this method is that co-cited documents have related claims, either by means of a agreement or disagreement, about a shared subject of research, and that the frequency of their co-citation scales proportionally to the relevance of their (combined) claims for a specific field of research (cf. Andersen, 2019; Dort, Strelow, French, et al., 2020). The importance of a document in the network was measured as a function of the importance of the documents it is often cited together with. To achieve this, we calculated the eigenvector centrality metric (Bonacich, 1987, 2007) for each document in the network. Eigenvector centrality is a measure of prestige for a node (e.g., a document) in a network (e.g., a co-citation network). Eigenvector centrality considers not just the number of connections a node has (i.e., its degree), but also the centrality of those nodes, with high scoring nodes counting more than low scoring nodes (cf. Golbeck, 2013, pp. 25–44). This method thus helps us identify seminal work in a field of research, providing an approximation of the intellectual or ideological bases thereof (Dort, Strelow, French, et al., 2020; Pasadeos et al., 1998).

Bibliographic coupling analyses

We estimated the relatedness of bibliographic objects based on how similar their reference lists were. In contrast to co-citation analysis, this method shows how closely related two documents are by looking at how many references they have in common. The logic here is that if two documents cite the same references, it is likely that their subject of research, or approach to a certain research question, is similar (Biscaro & Giupponi, 2014). In contrast, documents with fewer commonalities in their reference lists are assumed to be influenced by less interconnected bodies of research (Dort, Strelow, French, et al., 2020). Documents with high eigenvector centrality in their bibliographic coupling network provide representative reference lists for numerous connected publications, as they share substantial overlap in the research they refer to. In contrast to co-citation analysis, our bibliographic coupling analysis was limited to documents published between the years 2010 and 2020. We did this to achieve some basic level of similarity in the reference lists of the scientific documents, and to reduce systematic effects of the publication year, as the current literature cites both more recent publications and has a wider range of available resources to cite from (cf. Andersen et al., 2021).

Data clustering and visualization

Exploratory data analysis was carried out using the R package *bibliometrix* (Aria & Cuccurullo, 2017) and custom scripts written in the R programming environment (R Core Team, 2021). We carried out clustering and visualization taking the “visualization of similarities” approach (VOS; van Eck & Waltman, 2010) as implemented in VOS viewer software (version 1.6.16). The VOS technique relies on a matrix of normalized co-occurrences of items, such as keywords among journal articles or references in reference lists. For co-citation and bibliographic coupling analysis, we normalized the similarity matrix, and by extending the clustering, we relied on the association strength of items, defined as the ratio of co-occurrences between items in proportion to the total number of occurrences thereof (van Eck & Waltman, 2009, 2010). The mapping and visualization of the resulting clusters and networks was carried out as implemented in the VOS viewer. The VOS mapping

272 technique is closely related to multidimensional scaling (van Eck & Waltman, 2010), projecting a network into
273 two-dimensional space by placing nodes with high similarity (e.g., common relation to other nodes) closer to
274 each other.

Results

Our search identified a total of 1445 bibliographic objects from 353 different sources (e.g., journals, books). After removing meeting abstracts, news items, and documents with missing data (e.g., no reference lists), 1407 documents from 349 sources remained for analysis. Journal articles (i.e., research reports) were the largest group of documents ($N = 1212$), followed by reviews ($N = 102$), proceedings papers ($N = 51$), editorial material (22), and book chapters ($N = 20$). As depicted in **Figure 1**, the number of scientific publications related to expectation violations has risen exponentially in the time period 1990–2020 ($F(3,27) = 181.2$, $p < 2.2e-16$, $R^2 = 0.953$), with little variation in the number of documents published between the years 1990 and 2006 ($b_{\text{change}} = 1.37$, $SE = 0.43$) and sustained growth in scientific production between 2007 and 2020 ($b_{\text{change}} = 8.72$, $SE = 0.57$).

Figure 1

Number of publications per each year for the identified literature corpus.

Note. Solid dots depict the absolute number of publications.

Figure 2 shows the references with the most local citations (i.e., citations from within the identified literature corpus). Many of these references focused on how mesencephalic dopamine neurons encode reward prediction errors in the central nervous system (Montague et al., 1996; O'Doherty et al., 2004; Schultz, 1998; Schultz et al., 1997; Schultz & Dickinson, 2000), providing a biological proxy for the magnitude of the experienced expectation violation, and how higher brain areas use this information to respond in accordance with situational demands (Behrens et al., 2007; O'Doherty et al., 2003) and adjust behavior when situational outcomes are worse than expected (Botvinick et al., 2001; Gehring et al., 1993; Gehring & Willoughby, 2002; Holroyd & Coles, 2002; Miltner et al., 1997). Conversely, other documents focused on explaining variation in

the degree to which prediction errors lead to changes in behavior or experience (Pearce & Hall, 1980; Rescorla & Wagner, 1972) as well as on developing statistical (Friston, 2005, 2010) and computational (Sutton & Barto, 1998) frameworks and methods (Delorme & Makeig, 2004) to examine these phenomena. As depicted in **Figure 3**, analyses revealed that research focused on dopamine and frontal brain structures, such as the Anterior Cingulate Cortex (ACC), performance measures (e.g., behavioral responses, errors) and outcomes (e.g., rewards) have moved center stage. In addition, research focused on the processing of expectation violations in psychological disorders (e.g., obsessive-compulsive disorder – OCD, substance abuse, depression) and at different stages of human lifespan (e.g., childhood) have gained traction since 2010.

Figure 2

References with the highest number of citations from within the identified literature corpus.

Note. (1)= O'Doherty et al., 2003, (2) O'Doherty et al., 2004, (3) Rao & Ballard, 1999, (4)= Schultz, 1998

Figure 3

Trend topics for each year in the time range 2000-2020.

Note. Depicted are keywords with more than 5 occurrences and only the top 5 ranking keyword for each year. Abbreviations are “acc” = “anterior cingulate cortex”, “cbt” = “cognitive behavioural therapy”, “ern” = “error-related negativity”, “ltm” = “long term memory”, “stm” = “short term memory”, and “ocd” = “obsessive-compulsive disorder. (1) = judgment, (2) = identification, (3) = attribution, (4) = awareness, (5) communication, (6) = memory refers to “episodic memory” rather than general memory processes, (7) = language refers to “language comprehension” rather than general language related processes.

Co-citation network

Co-citation analysis revealed a total of 511 documents organized into five clusters. As depicted in **Figure 4**, cluster 1 (orange) was the biggest cluster of research containing 31.9% of the data, followed by cluster 2 (blue) containing 23.3%, cluster 3 (magenta) with 21.3%, cluster 4 (green) with 15.5%, and cluster 5 containing only 8% of the documents identified by co-citation analysis. Here we provide a description of these clusters ordered in accordance with the degree of their interconnections and relevance for the network (i.e., as opposed to ordering them by cluster size).

Figure 4

Visualization of the co-citation network

Note. Depicted are journal articles, books, and book chapters cited by the documents identified through the literature search. The size of the circles shows number of citations received by a reference (i.e., bigger nodes received more citations than smaller nodes). The proximity of the network nodes shows their relatedness, with nodes close to each other often appearing together in the reference lists of other documents. Cluster topics (clockwise from left): Blue cluster = “electrophysiological measures of brain activity and their relation to different kinds of expectation violations”, orange cluster = “phasic dopaminergic activity tracks the discrepancy between expected and obtained outcomes”, green cluster = “prediction errors drive learning by triggering expectation updating”, yellow cluster = “emotional and psychological reactions to expectation violations”, magenta cluster = “the brain processes prediction errors in accordance with a Bayesian scheme”. Node names were abbreviated to avoid overlap as much as possible. Digital object identifiers (DOIs) for the top-ranking nodes in each cluster are provided in Tables S1-S5.

Co-citation cluster 1 (orange) was located centrally in the network and was characterized by nodes with high eigenvector centrality, providing crucial links between other clusters of literature, most prominently cluster 2 (blue) and cluster 4 (green). In other words, literature in co-citation cluster 1 was heavily cited together with literature from co-citation clusters 2 (blue) and co-citation cluster 4 (green), even though publications from the latter two clusters were not cited together as frequently. Literature assigned to co-citation cluster 1 was dominated by research showing that phasic dopaminergic activity tracks the discrepancy between expected and obtained outcomes (e.g., Schultz et al., 1997) in accordance with a temporal-difference learning rule (cf. Sutton & Barto, 1998). A hallmark of this process is that the expected value of an action (or event) is updated dynamically as a function of the outcome information available, such as its (expected) outcome history (Daw et al., 2005). Co-citation cluster 2 (blue) was characterized by high density, as depicted by the high degree and closeness of its internal linkage (i.e., numerous interconnections within the cluster; Golbeck, 2013, pp. 25–44). This means that the cluster contains a closely interrelated set of literature typically cited by other literature from

within the cluster. Literature assigned to co-citation cluster 2 (blue) was dominated by research on electrophysiological measures of brain activity evoked by different kinds of expectation violations, such as ERPs following behavioral errors (Miltner et al., 1997) or performance feedback (Alexander & Brown, 2011), which indicate that the ACC is the main hub in a neural network that supports action outcome monitoring (Holroyd & Coles, 2002). In contrast, the distribution of co-citation cluster 4 (green) was more widespread. More precisely, there appeared to be two sub-clusters, of which one was more strongly associated with co-citation cluster 1 (orange). The most central documents in co-citation cluster 4 (green) focused on the modelling of how prediction errors drive learning by triggering expectation updating (e.g., Schultz & Dickinson, 2000) either by directly modulating the associative value of events (Rescorla & Wagner, 1972) or, more indirectly, by affecting the degree of attention allocated to the events associated with prediction errors (Pearce & Hall, 1980).

Co-citation cluster 3 (magenta) and co-citation cluster 5 (yellow) were located on the outer regions of the network and appeared to share some degree of overlap. Co-citation cluster 3 (magenta) was dominated by literature indicating that the statistical regularities of events are processed by the brain in accordance with a Bayesian scheme (Rao & Ballard, 1999; Yu & Dayan, 2005). The main idea here is that higher cortical structures provide guidance for lower-level processing areas by formulating expectations about bottom-up input. When these expectations are violated, lower cortical structures generate prediction error signals that can be used by higher brain structures to update expectations and reduce uncertainty in the future (cf. predictive coding; Friston, 2005). Conversely, the most influential documents in co-citation cluster 5 (yellow) concerned emotional and psychological reactions to expectation violations, such as strategies for compensating inconsistency between expectations and expectation-disconfirming evidence (Proulx et al., 2012), but also individuals' propensity to positive and negative affect (Watson et al., 1988) or sensitivity to rewards and punishments (Carver & White, 1994). In addition, this Co-citation Cluster 5 (yellow) included research on statistical procedures for evaluating and planning empirical studies, such as the computation and evaluation of statistical effect sizes and statistical power (Cohen, 1988; Faul et al., 2007).

Bibliographic coupling network

Bibliographic coupling analysis of documents published between 2010 and 2020 revealed a total of 454 interconnected nodes organized into six clusters (see **Figure 5**). Cluster 1 (orange) was the biggest, containing 29.3 % of the data, followed by cluster 2 (blue) containing 21.4 %, cluster 3 (magenta) with 18.5 %, cluster 4 (green) with 14.3 %, cluster 5 (yellow) containing 11.5 % of the documents, and cluster 6 (brown) containing only 5 % of the data. Here, clusters are described in accordance with their relevance for the network.

Figure 5

Visualization of the bibliographic coupling network

Note. Depicted are journal articles, books, and book chapters that were identified by our literature review. The size of the circles shows the number of citations received by a document (i.e., bigger nodes received more citations than smaller nodes). The proximity of the network nodes shows their relatedness, with nodes close to each other having more references in common in their reference lists (i.e., more similar reference lists). Cluster topics (clockwise from left): Brown cluster: “Expectation violations in early childhood”, orange cluster = “impact of expectation violations on social processes”, blue cluster = “predictive coding framework in clinical application”, magenta cluster = “prediction errors as the main mechanism for information sharing within the human brain”, green cluster = “the role of expectation violations for clinical practice”, yellow cluster = “biological markers for expectation violation”. Node names were abbreviated to avoid overlap as much as possible. Digital object identifiers (DOIs) for the top-ranking nodes in each cluster are provided in Tables S6-S11.

Bibliographic coupling cluster 3 (magenta) was the most central in the network. Literature assigned to coupling cluster 3 (magenta) was characterized by high eigen vector centrality, providing links for other clusters of literature, most prominently documents assigned to coupling cluster 4 (green) and coupling cluster 5 (yellow). The most central documents in coupling cluster 3 (magenta) were literature reviews indicating that prediction errors constitute the main mechanism for information sharing within the human brain (e.g., Den Ouden et al., 2012; Kim, 2013; Walsh & Anderson, 2014). A main claim in the studies is that prediction errors trigger information processing along different paths in the neural hierarchy (e.g., striatum, ventromedial prefrontal cortex; Walsh & Anderson, 2014) to support different types of learning (cf. model-free vs. model-based learning; Walsh & Anderson, 2014), giving rise to individual differences in preferential choice behaviors and cognitive control recruitment (Kim, 2013). Conversely, literature assigned to coupling cluster 4 (green) was

dominated by research that analyzed how different aspects of expectation violation (and its processing in the human brain) lead to better or worse learning. For instance, some studies (Greve et al., 2017) showed that larger and more precise prediction errors lead to better memory formation, while others (Moustafa et al., 2013) described dissociable brain circuits for processing the value and contextual information of aversive and appetitive stimuli. Coupling cluster 4 (green) also provided context for applying these findings in clinical practice (e.g., the role of expectation violations in fear extinction and exposure therapy; Craske et al., 2014). In contrast, research assigned to bibliographic coupling cluster 5 (yellow) focused on identifying candidate biological markers for assessing the impact of expectation violation on adaptive behavior (Cavanagh & Frank, 2014; San Martín, 2012; Ullsperger, Fischer, et al., 2014). Here, transient changes in the theta band of the EEG (Cavanagh & Frank, 2014) and ERP components, such as the FRN (Pfabigan et al., 2011) and P300 (San Martín, 2012), emerged as proxy measures for ongoing outcome processing (e.g., assessing value and predictability) and outcome-dependent behavioral adjustments (see Ullsperger, Danielmeier, et al., 2014 for review).

As depicted in **Figure 5**, bibliographic coupling clusters 1 (orange), 2 (blue) and 6 (brown) appeared less intertwined. The most central documents in coupling cluster 1 (orange) shared strong focus on the impact of expectation violations on social (i.e., interpersonal) processes (Harris & Fiske, 2010; Proulx et al., 2012; Proulx & Inzlicht, 2012). One set of articles focused on how inconsistencies between expected and experienced demands in social situations can evoke aversive cognitive and emotional states (Proulx et al., 2012; Proulx & Inzlicht, 2012), motivating compensatory mechanisms in multiple domains (e.g., behavior and experience; Randles et al., 2015). Results revealed strong connections between coupling cluster 1 (orange) and clusters 4 (magenta) and 5 (yellow), mainly mediated by studies focused on finding corresponding correlates of physiological activity that could help better characterize the effect of expectation violations in social contexts (e.g., Bell et al., 2016). In contrast, literature assigned to bibliographic cluster 2 (blue) focused on adaptations of the predictive coding framework (cf. Clark, 2013) for various fields of (clinical) application (e.g., treating depression: Chekroud, 2015; physical movement: Schiffer & Schubotz, 2011; selective deficits in autism: Van de Cruys et al., 2014). One main claim in coupling cluster 2 (blue) is that psychological disorders arise from maladaptive strategies for minimizing the impact of expectation violations, such as developing overly pessimistic expectations in the first place (e.g., negativistic beliefs in depression; Chekroud, 2015) or due to a lack of flexibility when coping with prediction errors (e.g., stereotyped behaviors in autism; Van de Cruys et al., 2014). Finally, bibliographic coupling cluster 6 (brown) appeared less consistently developed, with a subset of documents sparsely distributed across the network and a second more closely interrelated subset of documents located in the network's outer regions. Research in this sub-cluster of documents centered on the effects of prior experience on interpersonal expectation violations in early childhood (He et al., 2011; Sommerville et al., 2013; Träuble et al., 2010).

Discussion

Expectation violations have motivated a wide variety of research avenues within different fields of psychology. The present study describes how these research domains relate to each other and provides a scientific map that allows us to quantitatively assess their theoretical and empirical commonalities. Our goal was to inform future research projects by providing an overview of the most influential work in the field, helping researchers to identify links between different research domains such as empirical approaches, topics, and variables.

Our results revealed that the number of scientific publications related to expectations violations has increased exponentially since the early 2000s underlining the need for a comprehensive review. Indeed, many of the most frequently cited publications in the literature corpus were published in this time period (e.g., Friston, 2005; Gehring & Willoughby, 2002; Holroyd & Coles, 2002; Rao & Ballard, 1999; Schultz et al., 1997; Schultz & Dickinson, 2000). In addition, analyses of trend topics indicated that expectation violations have aroused scientific interest in multiple research areas, such as cognitive, biological, developmental, and clinical psychology. Furthermore, co-citation analyses revealed that many of the most cited articles in the literature corpus constituted a central node in the co-citation network, and that each these nodes was located in a different cluster (e.g., co-citation cluster 3 (magenta): Friston, 2005; co-citation cluster 2 (blue): Holroyd & Coles, 2002; co-citation cluster 1 (red): Schultz et al., 1997; co-citation cluster 4 (green): Schultz & Dickinson, 2000), providing the theoretical and empirical basis for separable research areas. Many of these often-cited scientific publications focused on different measures of neural activation (e.g., fMRI: Behrens et al., 2007; EEG/ERPs: Gehring & Willoughby, 2002; firing of dopamine neurons: Schultz & Dickinson, 2000) along with methods to analyze them (Delorme & Makeig, 2004), indicating that the ability to map the discrepancy between expected and observed outcomes to measurable indices of brain function has been one of the motors driving advancements in expectation violation research.

Expectation updating as a function of prediction errors

Co-citation analyses revealed that expectation violation research is grounded on the assumption that experiencing discrepancies between expectations and disconfirming evidence (i.e., prediction errors) is necessary for updating expectations, thus constituting the core mechanism of learning in general. However, the co-citation network also revealed that prediction errors do not necessarily serve the same function in different theoretical models and across different stages in the information-processing stream. For instance, co-citation cluster 4 (green) was dominated by the Rescorla-Wagner model (Rescorla & Wagner, 1972), where prediction errors drive changes in the predictive value of cues/events in a direct manner. Following Rescorla and Wagner (1972), large discrepancies between expected and observed outcomes (i.e., large prediction errors) will result in large changes in the associative value of the cues that predicted the outcome (e.g., certain situational characteristics). Furthermore, the sign of the prediction error (negative: outcome is worse than expected vs. positive: outcome is better than expected) determines the type of learning that takes place (e.g., the predictiveness of cues is reduced after negative prediction errors, thus leading to expectation change). Conversely, when the prediction error is zero, the outcome has been fully predicted and thus expectations do not change. In contrast, in Pearce and Hall's model (1980), also a prominent node in co-citation cluster 4 (green),

the absolute value of the prediction error determines how much attention is paid to the preceding cues when encountered in future situations, rather than changing their associative value directly. This “*attentional gain*” is believed to facilitate subsequent learning when the prediction error is large, and to inhibit learning when the prediction error is small. While the predictions of the Rescorla-Wagner and Pearce and Hall models might seem mutually exclusive, a growing body of research indicates that they might in fact play complementary roles (cf. Roesch et al., 2012). For instance, in the Rescorla-Wagner model, the degree to which prediction error leads to changes in expectations is scaled by free learning rate parameters potentially attributable to a mechanism like Pearce and Hall’s attentional gain (also see Mackintosh, 1975). In the co-citation network, literature addressing this issue was assigned to co-citation cluster 1 (red), demonstrating that research focusing on how different learning rules explain dynamic expectation updating (e.g., by integrating predictions from the Rescorla-Wagner and Pearce-Hall models; cf. Sutton & Barto, 1998) provide essential links between different research domains in the expectation violation literature.

Neural markers of expectation violation processing

Interestingly, numerous studies assigned to co-citation cluster 1 (red) indicate that the midbrain dopamine system’s activity provides an accurate measure of how signed prediction errors are processed by organisms (Frank et al., 2004; Pessiglione et al., 2006) in a dynamic (i.e., temporal difference) manner (O’Doherty et al., 2003). Here, dopaminergic activity has been shown to increase (i.e., neural activity bursts) in response to rewards. However, when an organism learns that a reward is predicted by a cue, dopamine bursts are increasingly elicited by the cue rather than by the rewarding outcome itself. In contrast, dopaminergic activity becomes weaker (i.e., neural activity dips) when the predicted reward is omitted, also leading to the preceding cue’s devaluation (Schultz et al., 1997). Co-citation cluster 1 (red), was dominated by studies implementing instrumental or classical (i.e., Pavlovian) learning paradigms (O’Doherty et al., 2003) and fMRI (Daw et al., 2011) to analyze how these processes influence the activity of higher cortical structures in the human brain. These studies show that in addition to the midbrain dopamine system, the medial prefrontal cortex plays a crucial role in action outcome prediction and valuation (Behrens et al., 2007). However, fMRI is limited by its poor temporal resolution (Carlson et al., 2011), in particular with regard to evaluating outcomes, which single-cell recordings in dopaminergic midbrain areas indicate is very constrained temporally (Fiorillo et al., 2003; Montague et al., 1996). Therefore, the ERP technique, which enables the analysis of outcome and prediction error processing at a much higher temporal resolution, has emerged as a prominent imaging alternative in the expectation violation literature. EEG/ERP literature was mostly assigned to co-citation cluster 2 (blue) and bibliographic cluster 5 (yellow). In these studies, salient and surprising events such as unexpected stimuli or outcomes have been shown to elicit amplitude modulation of the N2 and P3 ERP components (Baker & Holroyd, 2011; also see Ullsperger, Danielmeier, et al., 2014 for review). However, expectation violation research has been particularly interested in two other ERP components, namely the ERN (Gehring et al., 1993) and the FRN (Miltner et al., 1997). ERN and FRN are believed to reflect activity in the Anterior Cingulate Cortex (ACC), a structure in the Medial Prefrontal Cortex that is highly innervated by the midbrain dopamine system (Walsh & Anderson, 2014). The ERN is a transient negative deflection of the ERP that reaches its peak over frontal-central regions of the scalp within 100 ms from error commission in speeded response tasks.

Conversely, the FRN is a negative deflection of the ERP whose scalp topography resembles the ERN's and is elicited 200 – 400 ms after performance feedback, in particular when feedback is needed to estimate an action's value (cf. Hajcak et al., 2007). Research assigned to co-citation cluster 2 (blue) indicates that phasic dips in dopaminergic activity disinhibit neurons in the ACC, leading to negative shifts (i.e., increases) in FRN amplitude (Walsh & Anderson, 2014). In contrast, dopamine bursts inhibit the ACC, inducing positive shifts (i.e., decreases) in the FRN (Holroyd et al., 2008; Pfabigan et al., 2011). Moreover, drug-induced stimulation of the midbrain dopamine system has been shown to selectively affect the magnitude of these ERPs (de Bruijn et al., 2004; Santesso et al., 2009), indicating that fluctuations in ACC activity (indexed by ERN and FRN) act as an endogenous monitoring mechanism that uses prediction errors from lower brain structures to signal the need for adaptation in case of deviations from internally represented goals (Holroyd & Coles, 2002; Shenhav et al., 2013). Indeed, spectral analyses of ERP components like the N2, ERN, and FRN indicate that they are supported by synchronization in the EEG's theta frequency band following unexpected or motivationally salient events (Cavanagh & Frank, 2014), and that coupling in the theta frequency band facilitates communication across brain areas (Cavanagh & Frank, 2014). These findings converge in the assumption that prediction errors within higher cortical structures are influenced by prediction error signals elicited by lower cortical structures (Alexander & Brown, 2015). Furthermore, some studies suggest that higher-order prediction errors act as teaching signals for the system as it aims to gradually fine-tune the action-selection process to achieve better outcomes (Luque et al., 2012). In the expectation violation literature, this process is often referred to as predictive coding (Clark, 2013; Friston, 2005; Rao & Ballard, 1999). Predictive coding proposes that higher cortical structures use the prediction error generated by lower cortical areas to predict under which circumstances (e.g., situational cues) that prediction error is elicited. These higher-order representations (i.e., more abstract and generalized rules) are then used to modify lower order representations (i.e., less abstract anticipation of sensory information) to reduce the error margin of future predictions (Alexander & Brown, 2018). The updated higher-order representation of the environment is believed to integrate temporal and spatial information about immediate and distant influences on the prediction error, giving the organism the ability to update expectations dynamically and predict the consequences of future events (Clark, 2013). In the co-citation network, research focused on predictive coding was mostly assigned to co-citation cluster 3 (magenta).

Psychological responses to expectation violations

ERPs like the FRN are known to be sensitive to expectation violations in more complex contexts like interpersonal cooperation (Bell et al., 2016). In addition, research shows that personal factors that influence the experienced significance of these contexts lead to significant changes in performance monitoring ERPs (García Alanís et al., 2019; Mueller et al., 2014). Signals like the ERN and FRN therefore provide a valuable tool to assess the degree of arousal induced by expectation violations in a wide variety of contexts. Indeed, a growing body of literature considers how individual-level factors interact with situational characteristics to influence the psychological consequences of expectations violations (e.g., Rapp et al., 2021; Weinberg et al., 2016). While many of the studies have focused on expectation change following expectation violations, bibliographic coupling analysis revealed a separable subset of studies focusing on how expectations persist even when individuals encounter disconfirming evidence. For instance, Proulx and Inzlicht (2012) propose that the aversive

arousal evoked by expectation violation might be the key to understanding why and when expectations change. Proulx and colleagues (2017) showed that an aversive arousal is particularly evoked by expectations violations by measuring variations in pupillary dilation in response to expectation violating faces (i.e., presented upside-down and distorted). These stimuli produced pupillary dilation earlier than other faces (e.g., neutral, or threatening faces). In the Meaning Maintenance Model (MMM), Proulx and Inzlicht (2012) outline five different types of responses that either reduce or eliminate the source of the aversive arousal or reduce arousal without changing the original source (cf. Proulx et al., 2012). The first two responses are intended to reduce the discrepancy between an expectation and disconfirming experience: Individuals may reinterpret the experience in a way consistent with their beliefs (“*assimilation*”) or change the expectation post-hoc, so that it becomes consistent with the discrepant experience (“*accommodation*”). If individuals have no resources available to resolve the expectation violation (e.g., if accommodation or assimilation cannot be applied or do not work), the model postulates that the negative arousal elicited by expectation violations can be dispelled in one of three indirect ways (a process known as “*fluid compensation*”): Individuals either engage in heightened commitment to other (existing) expectations that have not been disconfirmed (“*affirmation*”), or they find (“*abstraction*”) or construct (“*assembly*”) expectations that have not been disconfirmed. In some cases, newly assembled expectations may also give meaning to the expectation violation (e.g., someone might think: “this happened for a reason”), reducing the significance of the original, violated expectation. Most of the research on the psychological responses to expectation violations focused on fluid compensation processes rather than on processes that directly reduce the discrepancy between an expectation and a disconfirming experience (cf. Randles et al., 2015).

On the relationship between basic and applied research

Regarding possible fields of application, translational clinical research has helped elucidate central mechanisms in psychopathology (e.g., anxiety disorders; Craske et al., 2018; Pittig & van den Berg, 2016). Cluster 4 (green) in the co-citation network captured recent studies that have successfully built on basic research knowledge to inform clinical applications. For example, Bach and colleagues (2010) applied classical learning theories and Dynamic Causal Modelling (a popular method within the predictive coding framework) to model fear-conditioned skin conductance responses – a marker of expectation strength in learned prediction processes (Hamm & Vaitl, 1996). Moreover, Abraham and colleagues (Abraham et al., 2014, 2016) showed that dopaminergic mechanisms of associative learning (as discussed in predictive coding and reinforcement learning research) play a crucial role in the development, generalization, and extinction of fear. Beyond highlighting the role of expectations and expectation change in the development and persistence of psychological symptoms and disorders (Rief et al., 2015), research in clinical psychology has moved towards applying these findings in psychotherapy. As expectations are among the strongest predictors of treatment outcomes in the treatment of various medical conditions, promising interventions focus on modifying patients’ dysfunctional expectations about their disorders and potential treatment effects (Craske et al., 2014; Doering et al., 2018; Rief & Glombiewski, 2016). Knowledge of the mechanisms that influence expectations’ persistence versus change has also led to the development of novel intervention methods in other fields, such as correcting stereotypes about

social groups (Dort, Strelow, Schwinger, et al., 2020; Zingora et al., 2020), a topic much less represented in expectation violation research, as the present bibliometric review reveals.

Limitations

The present bibliometric review provides an overview of research focused on expectation violation, expectation change, and expectation persistence. However, it is not necessarily a substitute for extensive literature surveys. Rather, the present bibliometric review provides complementary information to other, narrative, and systematic reviews focused on smaller and more specialized areas of research. More targeted reviews are necessary to assess whether and to what degree the psychological and neural mechanisms discussed here interact with individual-level and situational factors to influence the processing of expectation violating information (cf. Pinquart, Rothers, et al., 2021). One further limitation of the present study is that we did not analyze and could not monitor the quality of the discussed scientific publications (i.e., other than the controls required by the journals that published the studies). A challenge for future, more specialized reviews would be to analyze how the effects we have discussed on neural and psychological measures are consistent across a wide variety of studies (e.g., using meta-analytic approaches). Lastly, the present study is limited by its focus on a subset of data, as we only analyzed research published between 1990 and 2020 in the field of psychology. Other, more in-depth reviews may include the most recent publications and literature from adjacent fields of research, although the former might represent a challenge, as it takes time for scientific publications to be cited.

Conclusion

The present study is the first bibliometric review of expectation violation research. To the best of our knowledge, no other study has sought to quantitatively assess and map the structure of this growing body of research, providing an overview of the similarities and links between different subdomains. Our results show that, historically and currently, much of expectation violation research relies on associative learning theories that aim to explain how deviations from internally represented goal-states are processed by organisms, and what characteristics of expectation violating information make expectation change more probable. In addition, our results firmly demonstrate that biological markers, such as fluctuations in the activity of the midbrain dopamine system, in the activity of the ACC, and ERPs, such as the ERN, FRN, and the N2, can be seen as indices for expectation violation processing in the human brain, providing promising non-invasive methods to analyze expectation violations across a wide variety of experimental settings. The present study thus provides a broad perspective for expectation violation research, providing informative networks and clusters of literature for both scientists and practitioners who work across different areas of research, facilitating interdisciplinary advancements in the field of psychology.

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